Open Research Online

The Open University's repository of research publications and other research outputs

Scholarly insight 2016: a Data wrangler perspective

Other

How to cite:

Rienties, Bart; Edwards, Chris; Gaved, Mark; Marsh, Vicky; Herodotou, Christothea; Clow, Doug; Cross, Simon; Coughlan, Tim; Jones, Jan and Ullmann, Thomas (2016). Scholarly insight 2016: a Data wrangler perspective. Open University UK.

For guidance on citations see FAQs.

© [not recorded]

https://creativecommons.org/licenses/by-nc-nd/4.0/

Version: Version of Record

Copyright and Moral Rights for the articles on this site are retained by the individual authors and/or other copyright owners. For more information on Open Research Online's data policy on reuse of materials please consult the policies page.

oro.open.ac.uk

Scholarly insight 2016: a Data wrangler perspective

Bart Rienties, Chris Edwards, Mark Gaved, Vicky Marsh, Christothea Herodotou, Doug Clow, Simon Cross, Tim Coughlan, Jan Jones, and Thomas Ullmann

The Open University

Permission is granted under a Creative Commons Attribution Licence to copy, redistribute, remix, transform and build upon this report freely provided that attribution is provided as illustrated in the citation below. You may make changes in any reasonable manner, as long as you indicate that you have done this and do not imply that the licensor endorses you or your use. To view a copy of this licence, visit creativecommons.org/licenses/by/3.0

A full-text PDF version of this report is available to download from http://intranet6.open.ac.uk/iet/main/supporting-ou/data-wrangling

Dr Bart Rienties (Head Data wrangler and FBL Data wrangler)

Chris Edwards (FASS Data wrangler)

Dr Mark Gaved (FASS Data wrangler)

Vicky Marsh (FASS Data wrangler)

Dr Christothea Herodotou (FBL Data wrangler)

Dr Doug Clow (STEM Data wrangler)

Dr Simon Cross (STEM Data wrangler)

Dr Tim Coughlan (WELS Data wrangler)

Jan Jones (WELS Data wrangler)

Dr Thomas Ullmann (WELS Data wrangler)

Suggested citation:

Rienties, B., Edwards, C., Gaved, M., Marsh, V., Herodotou, C., Clow, D., Cross, S., Coughlan, T., Jones, J., Ullmann, T. (2016). *Scholarly insight 2016: a Data wrangler perspective*. Open University: Milton Keynes.

Institute of Educational Technology/Learning and Teaching Innovation, The Open University UK,

Walton Hall, Milton Keynes, MK7 6AA, United Kingdom

© The Open University, 2016

Contents

FOREWORD

We are pleased to offer you our first Scholarly insight 2016: a Data wrangler perspective. The OU is going through several fundamental changes, whereby strategic, pedagogical informed research and insight what drives student learning and academic performance is essential. Making sense of Big Data in particular can be a challenge, especially when data is stored at different data warehouses and require advanced statistical skills to interpret complex patterns of data. In 2012 the Open University UK (OU) instigated a Data Wrangling initiative, which provided every Faculty with a dedicated academic with expertise in data analysis and whose task is to provide strategic, pedagogical, and sense-making advice to staff and senior management. Given substantial changes within the OU over the last 18 months (e.g., new Faculty structure, real-time dashboards, increased reliance on analytics), an extensive discussion with various stakeholders within the Faculties was initiated to make sure that data wranglers provide effective pedagogical insight based upon best practice and evidence-based analyses and research (see new Data wrangler structure).

Demand for actionable insights to help support OU staff and senior management in particular with module and qualification design is currently strong (Miller & Mork, 2013), especially a desire for evidence of impact of "what works" (Ferguson, Brasher, et al., 2016). Learning analytics are now increasingly taken into consideration when designing, writing and revising modules, and in the evaluation of specific teaching approaches and technologies (Rienties, Boroowa, et al., 2016). A range of data interrogation and visualization tools developed by the OU supports this (Calvert, 2014; Toetenel & Rienties, 2016b).

With the new ways of working with Data Wrangling, first we have provided our basic statistical analyses in form of our Key Metrics report. Second, from January 2017 onwards we will focus again on dealing with bespoke requests from Faculties, and where possible share the insights across all Schools and Faculties. Third, this Scholarly insight has a different purpose to previous Data wrangler work, namely **we aim to provide state-of-the-art and forward looking insights into what drives our students and staff in terms of learning and learning success**. Based upon consultation with the Faculties, seven key cross-Faculty themes were identified that influence our students' learning experiences, academic performance, and retention. The first five chapters focus on how the OU designs modules, formative and summative assessments and feedback, helps students from informal to formal learning, and how these learning designs influence student satisfaction. All five chapters indicate that the way we design our modules fundamentally influences student satisfaction, and perhaps more importantly academic retention. Clear guidelines and good-reads are provided for how module teams, ALs, and others can improve our focus on *Students First*. In Chapter 6-7, we specifically address how individual student demographics (e.g., age, ethnicity, prior education) and accessibility in particular influence the students' learning journeys, with concrete suggestions how to support our diverse groups of students. **Note that each chapter can be read independently and in any particular order. We are looking forward to your feedback.**

Bart Rienties, Chris Edwards, Mark Gaved, Vicky Marsh, Christothea Herodotou, Doug Clow, Simon Cross, Tim Coughlan, Jan Jones, and Thomas Ullmann.

EXECUTIVE SUMMARY

1. Learning design

Conole (2012, p. 121) describes *learning design* as “a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies”. Learning design is focussed on ‘what students do’ as part of their learning, rather than the ‘teaching’ which is focussed on the content that will be delivered. Within the OU, there is an increased recognition that learning design is an essential driver for learning (Rienties & Toetenel, 2016; Rienties, Toetenel, & Bryan, 2015; Toetenel & Rienties, 2016a; Whitelock & Rienties, 2016)

Although learning design is widely studied as a way to improve module designs (Armellini & Aiyegbayo, 2010; Koedinger, Booth, & Klahr, 2013; MacLean & Scott, 2011), few institutions with a notable exception of the OU have captured and updated these data in order to reflect on how these modules are delivered to students. Recent research and practical experience at the OU indicates that learning design has a fundamental influence on our students’ learning behaviour, their satisfaction of the module, and most importantly pass-rates. For example, Rienties and Toetenel (2016) linked 151 modules taught in 2012-2015 at the OU followed by 111,256 students with students’ behaviour using multiple regression models and found that learning designs strongly predicted Virtual Learning Environment (VLE) behaviour and performance of students. The primary predictor of academic retention was the relative amount of communication activities (e.g., student to student interaction, student to teacher).

Toetenel and Rienties (2016a) found that on average students were expected to spend 21.50% of their study on assessment, although substantial variation (range 0-78%) was found amongst these modules when comparing 157 modules at the OU. A vast range of designs are present at the OU, but most of them use a relatively high focus on assimilative and assessment learning activities, with relatively lower usage of more student-active activities (e.g., finding information, communication, productive). The way that OU staff design courses can be effectively supported with learning design. When OU members of staff were given visualisations of their initial learning design activities, they adjusted their designs towards more student-active activities, such as communication and finding information, while reducing the emphasis on assimilative activities (Toetenel & Rienties, 2016b). These Big Data findings indicate that a key to solve the OU retention problem is to revisit the learning designs of modules and qualifications, see Chapter 1 Learning design.

2. Student satisfaction

The introduction of the Teaching Excellence Framework (TEF: J. Johnson, 2015) signals a move for the higher education sector into a more competitive market, and with this student satisfaction has become an important component of Quality Assurance (QA) and Quality Enhancement (QE). The measurement of student satisfaction is important to higher education institutions, to help them to pinpoint their strengths and identify areas for improvement

(Moskal, Stein, & Golding, 2015; Zerihun, Beishuizen, & Os, 2012) and is now intrinsically related to their TEF rating, as satisfaction surveys are key TEF metrics.

A key concern for most institutions and teachers is whether students, or learners in general, are satisfied with their learning experience (Kember & Ginns, 2012; Marsh, 1982; Onwuegbuzie et al., 2007). Besides the obvious long-term advantages of having "satisfied customers", who are more likely to return for follow-up education or who share their positive experiences with peers (Gu, Schweisfurth, & Day, 2010; Li, Marsh, & Rienties, 2016), an increasing number of institutions are using internal and external student evaluation instruments to monitor and improve their teaching and learning experience (Arbaugh, 2014; Eom & Ashill, 2016; Rienties, 2014).

The Student Experience on a Module (SEaM) institutional survey was introduced in 2012/13 combining two previous surveys using a census approach, inviting all students on all modules to participate. Module pass rate data is systematically collected by the university administrative systems. OU analysis (Li, Marsh, & Rienties, 2016; Li, Marsh, Rienties, & Whitelock, 2016) has evaluated the 15 key drivers for module satisfaction and module performance data in order to inform principles of good practice in learning design. Li, Marsh, Rienties, et al. (2016) carried out a study of 422 undergraduate OU modules that involved logistical regression modelling of learner satisfaction using 232 variables including learning design, learner characteristics and assessment types. The findings indicated that learning design has a strong and significant impact on overall satisfaction, for both new and continuing learners. OU students who were more satisfied with the quality of teaching materials, assessment strategies, and workload were more satisfied with the overall learning experience. Furthermore, long-term goals of learners (i.e., qualifications and relevance of modules with learners' professional careers) were important predictors for learner satisfaction. Individual learner characteristics were mostly insignificant, indicating that despite a wide diversity of learners studying at the OU the underlying learning experiences were similar. As was found in Chapter 1 Learning design, the way we design OU modules and qualifications significantly predict our student satisfaction. For the list of 15 key drivers, see Chapter 2 Student satisfaction.

3. Summative Assessment and Feedback

Summative assessment is used throughout higher education and an increasing number of institutions are now using Computer Based Assessments (CBA) to deliver, monitor, and evaluate assessment of learning (Bearman et al., 2016; Boud & Falchikov, 2006; Tempelaar, Rienties, & Giesbers, 2015). CBA is often used for aptitude tests, and feedback from this type of test is conventionally limited to a grade (Boud & Falchikov, 2006; Ras, Whitelock, & Kalz, 2015). A limitation of the summative approach, which assesses what has been learned, is that students only receive feedback once they have completed all their learning activities (Segers, Dochy, & Cascallar, 2003). Formative assessment (see Chapter 4) has an entirely different function – it is used to inform students and educators (Segers et al., 2003) about student progress. It provides information that can help to shape learning, and is particularly useful when it is available to learners either before they start work or during the learning process.

The base data gathered for summative assessment are the marks awarded to students, but there a wide range of other data is gathered too, including the times of submissions and marks, the assessment requirements (thresholds, compulsory/optional), and information relating to matters such as special circumstances, deferrals/postponements, and assessment banking. The data are reported in a range of ways, particularly pass rates and z-scores, chiefly through the Annual Quality Review (AQR) process and the IET Student Statistics tools. The literature on assessment is extensive. Key points are the fundamental importance of assessment, concerns about validity and reliability, attainment gaps across different groups, and a shift away from examinations in favour of coursework. There is a need to explore further the data on End of Module Assessments (EMAs) compared to exams, and to evaluate the Single Assessment Component pilots, where there is no examinable component. There is scope for better understanding students who complete their Overall Continuous Assessment Score (OCAS) but do not sit the exam or submit their EMA. As indicated in Chapter 3, assessment banking warrants further investigation, and there may be scope for more rigorous exploration of reliability of marking.

4. Formative Assessment and Feedback

Formative assessment "is a systematic process to continuously gather evidence about learning" (Heritage, 2007), providing feedback to students on assessed work in a manner that promotes learning and facilitates improvement (Quality Assurance Agency, 2000). The goal is to enable learners to have "a better understanding of what they are trying to learn, what is expected of them and how to make improvements" (Daly, Pachler, Mor, & Mellar, 2010). Whitelock (2007, p. 492) argued that formative assessment helps to "shape learners as independent thinkers, making their own judgements and decisions about their learning in partnership with their peers and tutors".

A student-centred and social constructivist model of learning identifies students as playing an active role in the learning and the assessment process (Palincsar, 2005). Self-regulation and empowerment are central, implying that "the student has in mind some goals to be achieved against which performance can be compared and assessed" (Nicol & Macfarlane-Dick, 2006, p. 200), which in a formal learning environment are often structured by external reference points, such as specific targets, criteria, and standards. Formative assessment is distinguished from summative assessment by being validated in terms of its consequences as much as their meanings (Wiliam & Black, 1996).

Within the OU, the term formative is used to describe an assignment that has a zero weighting (no credit is gained). In general, this type of assignment is provided for teaching purposes only and has no direct impact on OCAS; however formative assignments can have a threshold attached to them and/or be made compulsory (OU Teaching and assessment strategy guidance). Increasingly since 2012, OU students are from groups "historically found to be less confident and prepared for distance mode HE study", and such students "have little tacit knowledge and understanding of assessment literacies" (Evans, Jordan, & Wolfenden, 2016). Therefore, formative assessments can help students develop these literacies and prepare for summative assessment. Finally, with the emergence of MOOCs (Massive Open Online

Courses) that are awarded no credit, there is increased interest in formative assessment and how this might be used to support learning. See Chapter 4 for some useful examples how to effectively design and integrate formative assessment.

5. From informal to formal learning

From its inception in 1969 the OU has provided a route from *informal* to *formal* learning, introducing the possibility of university study to many people. This is embodied in the OU's mission which remains "The OU is open to people, places, methods and ideas" (Open University, 2012). It is relatively recently that an institutional objective was set to ensure "World leadership in delivering journeys from informal to formal learning through open media" (Open University, 2012). Although the University Strategy has been redefined as *Students First: Strategy for Growth* (Open University, 2016), there remains a strong commitment to developing digital platforms with attractive content to engage learners. Our initial overview of *informal* to *formal* learning finds there is not universal agreement in the way these terms are used, and there continues to be discussion on the best use of a several terms to cover the range of different learning models from implicit, learning without thinking, to the successful completion of a carefully designed, quality assured, course leading to the award of credit and a qualification.

Providing full data on learners' journeys from informal to formal learning for module teams and subject groups is still to be fulfilled, in particular in terms of returns on investment and longitudinal analyses of successful transition, although this is progressing. The recent linking of data to allow journeys to be followed beyond enquiry has been a significant step in achieving this (Law & Jelfs, 2016). One recent development in OpenLearn has been the move towards Badged Open Courses, BOCs, which are expected to not only provide informal students something they will value but also encourage a greater proportion into formal study, and data from these will provide useful to faculties. By explicitly maintaining a strong focus on enabling and encouraging students to move from *informal* learning to *formal* OU study, the OU is keeping true to its mission and engaging in a rich and developing set of new technologies and practices which have a strong potential to impact on the health of the Institution and enhance the student experience. See Chapter 5 for the latest on from informal to formal learning.

6 Student demographics impacting retention

Understanding the relationships between student demographics and retention has been a longstanding issue of interest within the OU (Calvert, 2014; Cooper, Ferguson, & Wolff, 2016; Jelfs & Richardson, 2010; Li, Marsh, & Rienties, 2016; Richardson, 2009a, 2009b). A range of systems (AL tutor home, Strategy Information Office, SAS Visual Analytics) have been developed that aggregate student information and provide static or (near) live insights as to how specific cohorts or individual students "behave" within a specific module or qualification. These systems make use of a range of student demographic data, so-called learner data such as age, gender, prior assessment results, as well as learning data, such as VLE activity, completion and pass rates to inform the OU as to which students require special attention, monitoring or to intervene in order to ensure that they will not fail their studies. Three main sources of information are available: (a) the SAS Visual Analytics system providing a view of student progression and retention across the OU, faculties, qualifications and modules, (b) OU Analyse a predictive learning analytics tool that uses a range of advanced statistical and machine learning approaches to predict students at-risk and improve the retention of OU students and (c) data in the SST website hosting a range of information about student demographics and retention at module and qualification levels and related tools used to explore trends within specific modules or qualifications. In Chapter 6 our Scholarly insight indicates that demographic characteristics substantially influence student progression and retention, and our current systems allow ALs, module teams, and senior management to specifically drill into learning metrics to support groups of learners who may need additional support.

7. Accessibility

Analysis of accessibility of OU study entails understanding the attainment and experiences of disabled students, and their interactions with materials, systems, staff, and support services. OU students declaring a disability comprise an increasing proportion of overall student registrations, from 4.18% in 2010/11, to 16.53% in 2015/16. It is paramount to see disabled students as a core part of the OU student population and to continually evaluate our provision for them.

While accessibility is often viewed in terms of technical standards and guidelines, it is really a combination of social, pedagogical, and technical processes (Cooper, Sloan, Kelly, & Lewthwaite, 2012) where the diverse contexts of individual students need to be taken into account (Sloan et al., 2006). As such, accessibility should be evaluated and improved through attention to multiple data sources. Achieving accessibility in OU modules requires answers to questions such as: Is an image integral to a particular learning activity? If so, is there an alternative form of activity for students with sight disabilities? If a student requests an audiobook version of their materials, is this made available to them in a timely manner? If an activity requires interaction between students, might some students be unable to take part and therefore withdraw or fail? These issues are tackled through two approaches: designing modules and qualifications to be accessible at the production stage, and making responsive adjustments and support available according to student needs at the presentation stage.

There is evidence that disabled students in HE can perform as well as non-disabled students (e.g., Richardson, 2009a), particularly where support is received (HEFCE, 2015a). However, there is a persistent and large gap in OU module completion between students declaring a disability and the rest of the student population. This stood at 6 percentage points in 2010 but has risen to 11-12 points for the past three years. Learning analytics should be used to identify areas requiring attention in our courses (e.g., Cooper et al., 2016; Rienties, Boroowa, et al., 2016; Toetenel & Rienties, 2016a), and with regards to our provision for particular disability types (Richardson, 2015b). In addition, sources of data from OU processes and student feedback should be harnessed to evaluate our performance holistically, and to understand where we can improve. For a detailed analysis of effective accessibility support, see Chapter 7 Accessibility.

1. LEARNING DESIGN

1) How is learning design measured at the OU

The learning design taxonomy was developed as a result of the Jisc-sponsored OU Learning Design Initiative (OULDI) (Cross, Galley, Brasher, & Weller, 2012), and was developed over five years in consultation with eight Higher Education institutions. In contrast to instructional design, learning design is process based (Conole, 2012); following a collaborative design approach in which OU module teams, curriculum managers, and other stakeholders make informed design decisions with a pedagogical focus through using representations in order to build a shared vision. The OU uses seven learning activities to categorise learning design, as indicated in Table 1.

Table 1. Learning design activities

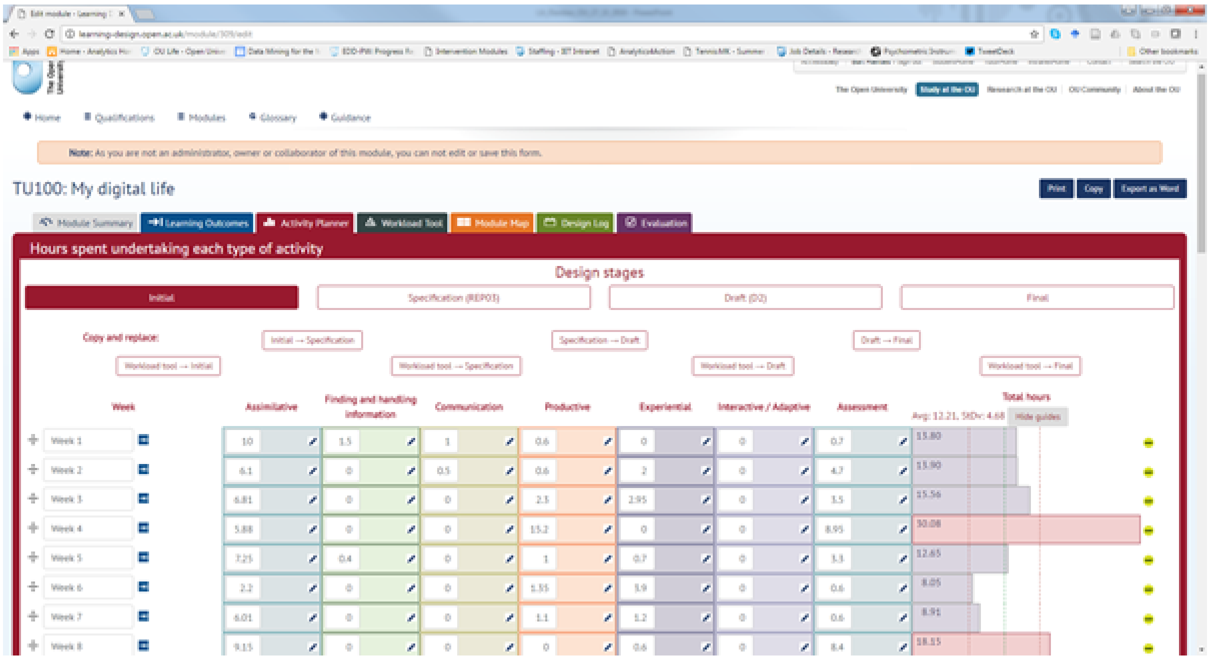
	Type of activity	Example
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access.
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather.
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe.
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete,
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate,
Interactive/adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate.
Assessment	All forms of assessment (summative, formative and self-assessment)	Write, Present, Report, Demonstrate, Critique.

Source: http://learning-design.open.ac.uk/

Assimilative activities relate to tasks in which learners attend to discipline specific information. These include reading text (online or offline), watching videos, or listening to an audio file. By *finding and handling information*, for example on the internet or in a spreadsheet, learners take responsibility for their learning, which is also focused on skills development in contrast to teacher-driven content. *Communicative activities* refer to any activities in which students communicate with another person about module content. *Productive activities* refer to activities whereby learners build and co-construct new artefacts. *Experimental activities* provide learners with the opportunity to apply their learning to a real life setting. *Interactive activities* endeavour to do the same, but in a safe setting, such as provided through simulations. Finally, *assessment activities* encompass all learning materials focused on assessment to monitor (formative) progress and/or traditional assessment for measurement purposes.

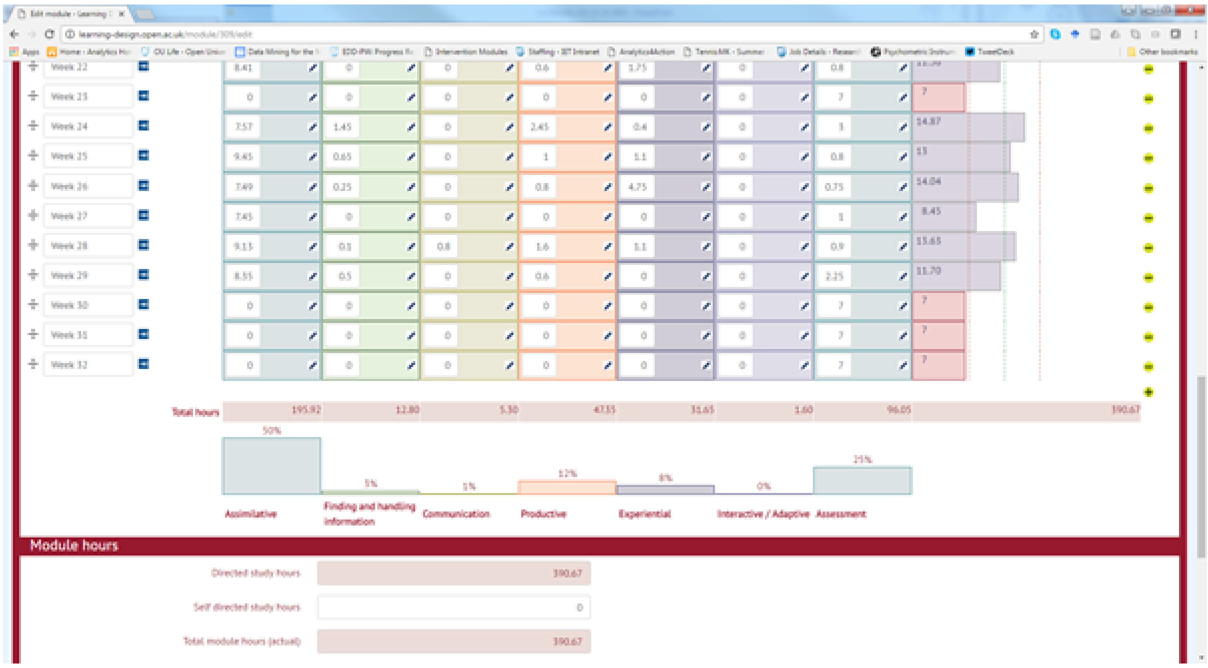
For each activity per week, an estimation is made as to how long it would take an average student to complete the respective activity. Of course in practice it might be that some activities (e.g., watching a 5 minute video with questions afterwards, reading 500 words on a Shakespeare play, finding out why global warming in Costa Rica has accelerated in the last five years) might take longer for some students, while for others these activities can be completed quicker. In principle each module mapping can be updated by module teams every presentation. Module teams can easily copy-paste their module mapping on http://learning-design.open.ac.uk/ and adjust the timing and activities accordingly where needed.

Figure 1 Module activities within a level 1 module (overview of first 8 weeks)



A process of "module mapping" or "coding learning activities" (i.e. analysing and providing visualizations of the learning activities and resources involved in a module) was introduced at the OU which aims to use learning design data for quality enhancement. In addition to this institution-wide focus, academic colleagues in faculties often request for their modules to be mapped, in particular when reviewing or redesigning their courses. The mapping process is comprehensive, but labour intensive; typically taking between three and five days for a single module, depending on the module's number of credits, structure, and quantity of learning resources. A team of learning design specialists within IET/LTI reviews all the available learning materials, classifies the types of activity, and quantifies the time that students are expected to spend on each activity, as illustrated in Figure 1 and Figure 2.

Figure 2 Module activities as a whole and in last weeks of course

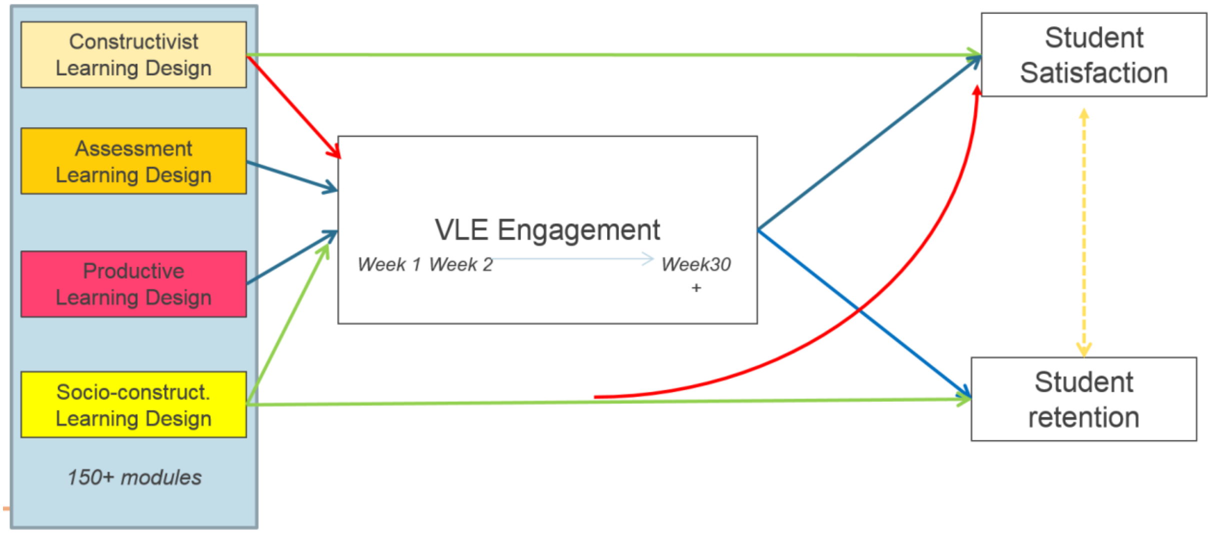


Classifying learner activity can be subjective, and consistency is important when using the data to compare module designs across disciplines in the institution. Therefore, the learning design team holds regular meetings to improve consistency across team members in the mapping process. Once the mapping process is complete, the learning design team manager will review the module before the findings are sent to the faculty. Some faculties have also mapped the modules themselves in order to compare both data sets. OU staff have the opportunity to comment on the data before the status of the design is finalised. In other words, each mapping is commonly reviewed by at least three people, which enhances the reliability and robustness of the data relating to each learning design. The learning design tool at the OU is a combination of graphical, text-based tools that are used in conjunction with learning design workshop activities. In total 259 modules have thus far been mapped by the learning design team. If module teams or OU staff want to know more about learning design, feel free to contact them directly at http://intranet6.open.ac.uk/teaching/learning-design/.

2) How does learning design influence student performance and satisfaction?

Several recent articles have been produced by the OU/IET that highlight the importance of learning design. Below we provide a short summary of each article, and how these findings can be used to support module design and active presentation. Rienties and Toetenel (2016)linked 151 modules taught in 2012-2015 at the OU followed by 111,256 students with students' behaviour using multiple regression models and found that learning designs strongly predicted VLE behaviour and performance of students. As illustrated in Figure 3, the primary predictor of academic retention was the relative amount of communication activities. This may be an important finding as in particular in online learning there tends to be a focus on designing for cognition rather than social learning activities (Arbaugh, 2014; Koedinger et al., 2013), while recently several researchers have encouraged teachers and researchers to focus on the social elements of learning (Arbaugh, 2014; Ferguson & Buckingham Shum, 2012).

Figure 3 Learning design strongly influences student behaviour, satisfaction and performance

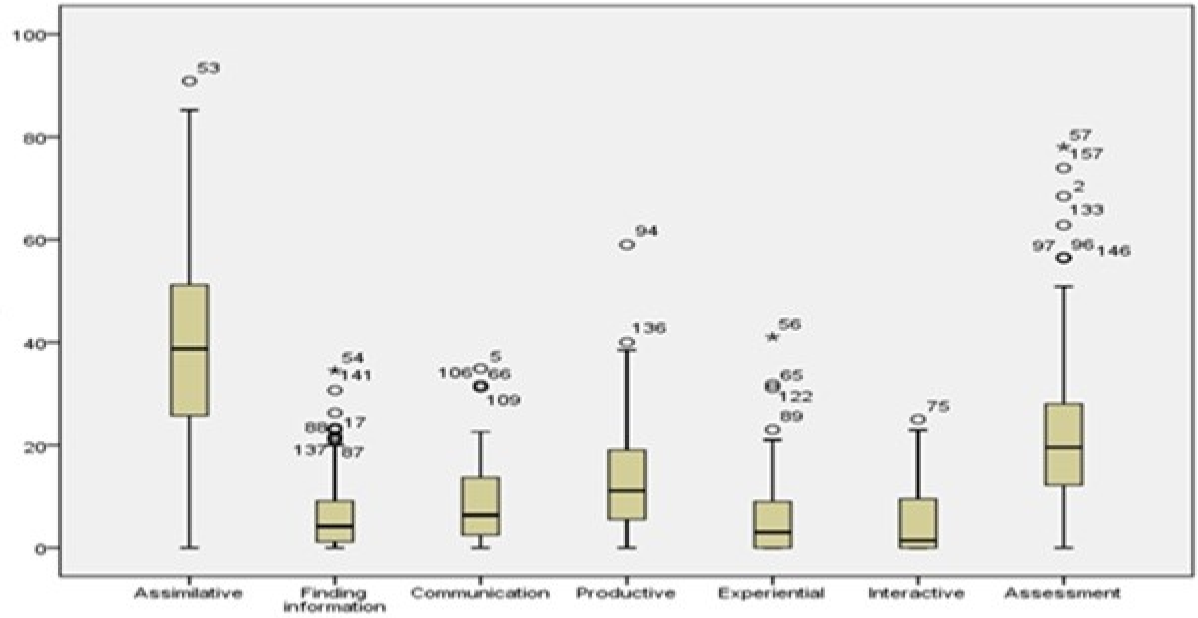


Source: Rienties and Toetenel (2016)

A second important finding was that learner satisfaction was strongly influenced by learning design (Rienties & Toetenel, 2016). Modules with assimilative activities and fewer student-centred approaches like finding information activities (i.e., Constructivist learning designs) received significantly higher evaluation scores. However, a crucial word of caution is in place here. Although we agree with others (Arbaugh, 2014; Onwuegbuzie et al., 2007; Zerihun et al., 2012) that learner satisfaction and happiness of students is important, it is remarkable that learner satisfaction and academic retention were not even mildly related to each other in Figure 3. Given that students who complete the SEAM questionnaire are a sub-set of the entire cohort of students, and students who drop out at the beginning of the module are less likely to complete SEAM, one has to be careful in interpreting these findings (see Chapter 2). More importantly, the (student-centred) learning design activities that had a negative effect on learner experience had a neutral to even positive effect on academic retention. The primary predictor for retention was communication, so when designing modules OU staff will have to strike a delicate balance between "happy" students and retention.

In a study comparing 157 learning designs at the OU, Toetenel and Rienties (2016a) found that on average students were expected to spend 21.50% of their study on assessment, although substantial variation (SD = 14.58%, range 0-78%) was found amongst these modules when comparing 157 modules at the OU. As highlighted in Figure 4, a vast range of designs are present at the OU, but most of them use a relatively high focus on assimilative and assessment learning activities, with relatively lower usage of more student-active activities (e.g., finding information, communication, productive).

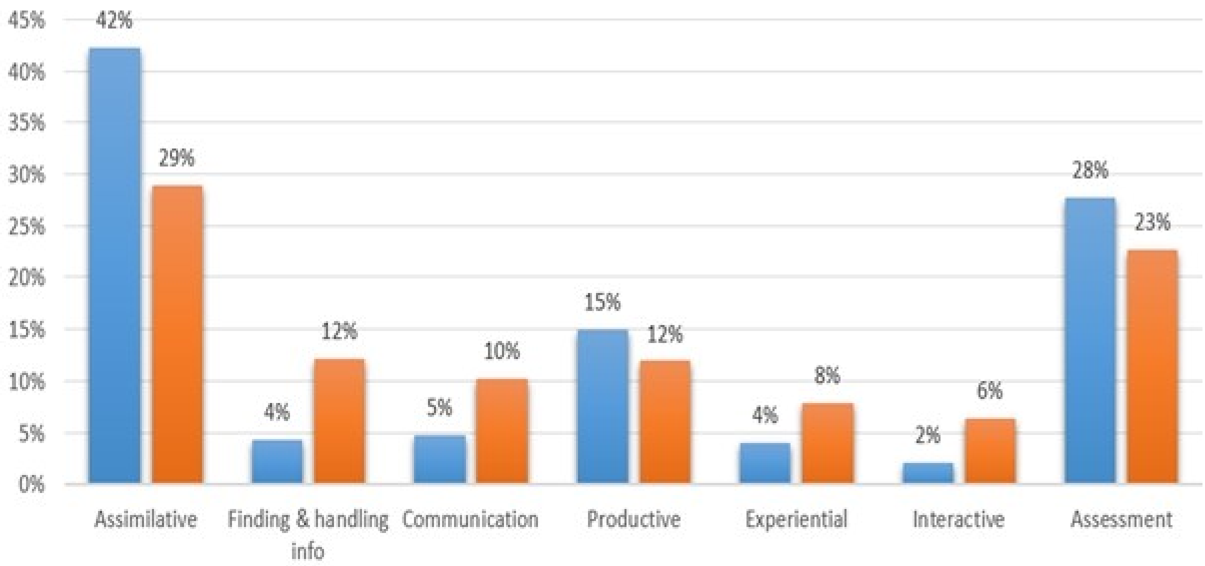
Figure 4 Boxplot of seven learning design activities of 157 courses (in percentages)



Source: Toetenel and Rienties (2016a)

In a follow-up study of 148 learning designs by Toetenel and Rienties (2016b), the introduction of a systematic learning design initiative consisting of visualization of initial LDs and workshops helped educators to focus on the development of a range of skills and more balanced LDs. As illustrated in Figure 5, when OU members of staff were given visualisations of their initial learning design activities, they adjusted their designs towards more student-active activities such as communication and finding information, while reducing the emphasis on assimilative.

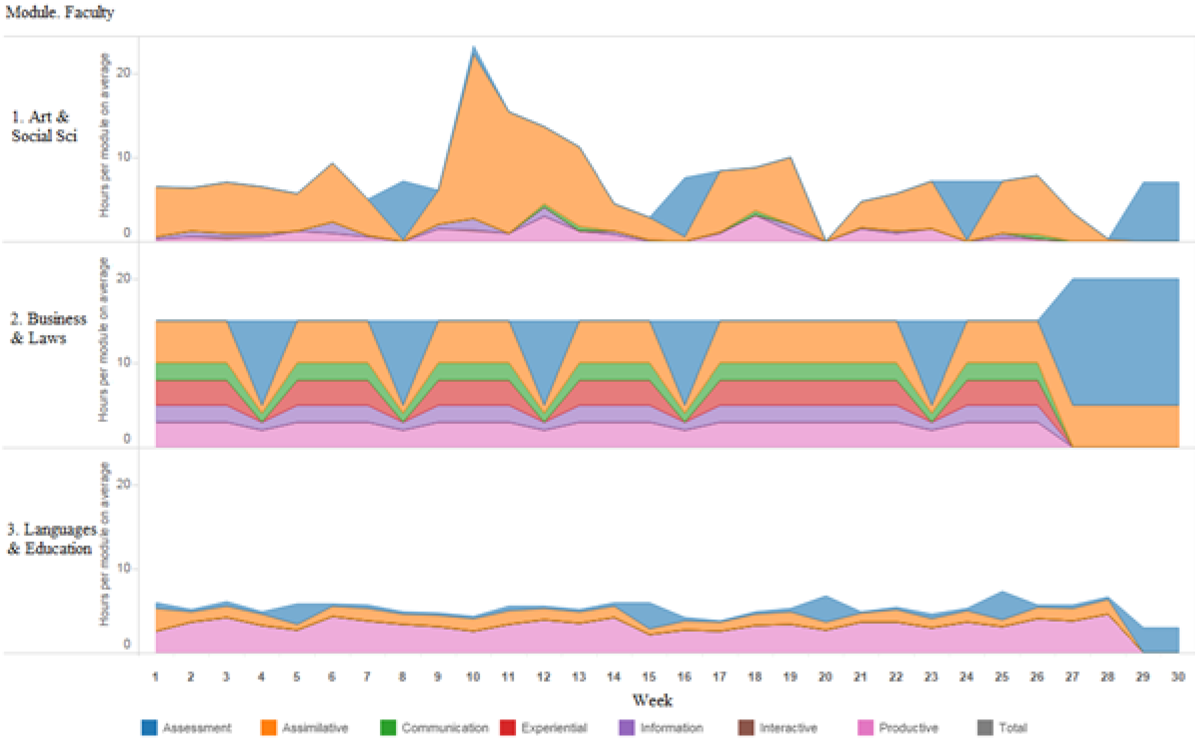
Figure 5 Changing learning design of OU teachers (before and after visualisations)



Source: Toetenel and Rienties (2016b)

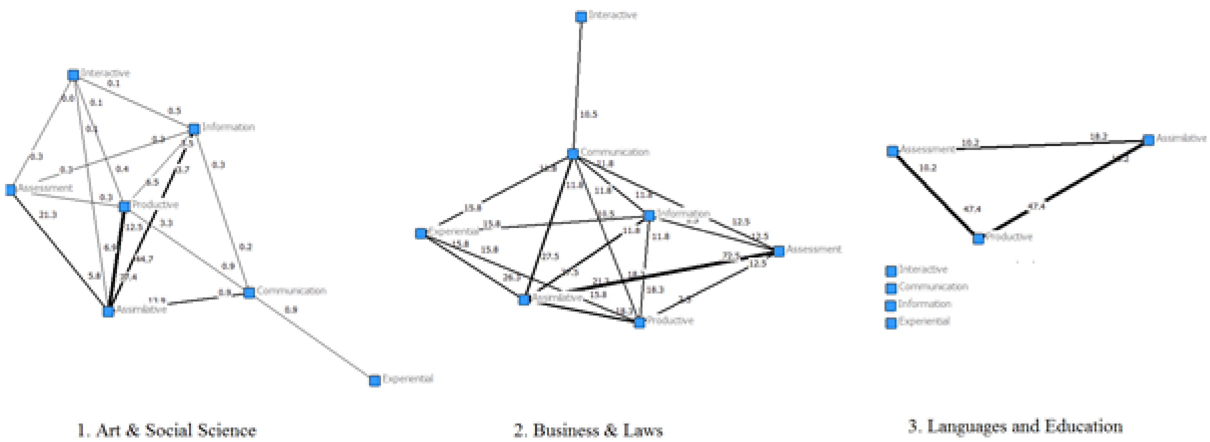
A recent PhD study by [Nguyen, Rienties, and Toetenel (2017)](#) on longitudinal design decisions by OU staff indicated that learning design activities per week significantly predict VLE behaviour per week and pass rates at the end of the module. As indicated in Figure 6, substantial variation in learning design activities per week exist between modules, as illustrated by these three modules. Follow-up analysis of the types of activities used in these three modules indicate a mix of activities, as illustrated in Figure 7. In other words, how OU teams design their modules have a substantial impact on student engagement.

Figure 6 Learning design per week across three modules



Source: [Nguyen et al. (2017)](#)

Figure 7 Learning design activities per module.



Source: [Nguyen et al. (2017)](#)

3) Which metrics are missing in learning design?

Although substantial amounts of data on expected workloads on the seven learning activities are present, specific details about the specific tasks are currently not coded explicitly. For example, formative assessment activities such as ICMAs or peer feedback are coded in a similar manner as summative assessment activities, such as final exam. Similarly, the type of communication activities (student to student, student to group, student to teacher) are aggregated on one activity, while fine-grained data about the types of interactions would help to unpack which learning design activities in terms of communication really help to increase retention. The learning design team is currently working towards more fine-grained recording of activities.

4) Good reads

Rienties, B., & Toetenel, L. (2016). The impact of learning design on student behaviour, satisfaction and performance: a cross-institutional comparison across 151 modules. *Computers in Human Behavior, 60*, 333-341. doi: 10.1016/j.chb.2016.02.074

Available at http://bit.ly/2gX8sfL

This article compared the learning designs of 151 modules across the four Faculties and indicates that learning design significantly predicts student behavior, satisfaction, and pass-rates.

Toetenel, L., & Rienties, B. (2016). Learning Design – creative design to visualise learning activities. *Open Learning, 31*(3), 233-244. doi: 10.1080/02680513.2016.1213626.

Available at http://bit.ly/2hOSKFR

This article illustrates that by providing visualisations to OU teachers of their learning design decisions and discussing these choices, more student-centred designs were developed with less focus on assimilative activities.

2. STUDENT SATISFACTION

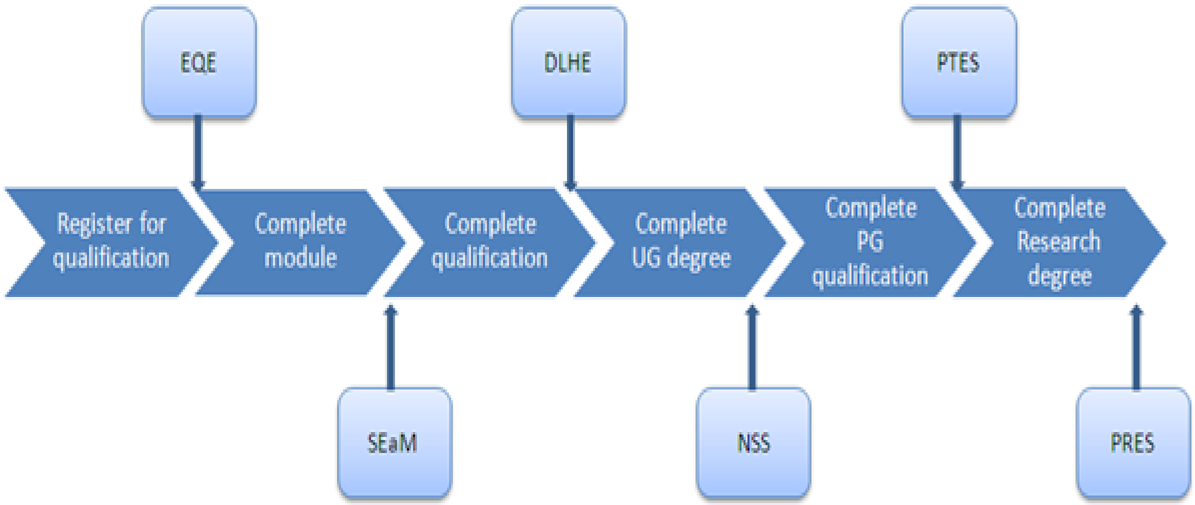
1) How does the OU measure student satisfaction

The OU participates in a number of external surveys with the purpose of gathering UK wide satisfaction data for particular groups of students. There are a number of different survey instruments that have been developed in order to capture student feedback; the most well known in the UK is the National Student Satisfaction survey (NSS). This survey is distributed to all students as they come to the end of their undergraduate study, and is used as a benchmark for evaluating institutional student satisfaction. Results are published nationally and so the media publish league tables allowing potential students to compare institutions. More detailed results are also released as part of national 'Key Information Sets' providing comparative undergraduate information across institutions via the Unistats website which is aimed at prospective students. Table 2 summarises the detail for each of the survey instruments that the OU regularly participates in. SEaM and EQE are instruments that have been developed and are administered internally. As illustrated in Figure 8, each of the survey instruments detailed above are aimed at a slightly different target population of students, and are intended to capture satisfaction at different stages of the student journey.

Table 2: OU Institutional survey target populations

Survey	Acronym	Who	When	Mode	Frequency	Distribution
National Student Survey	NSS	UG	120+ credits after 3 years of study	Web TEL	Annual	Jan-April
Postgraduate Taught Experience Survey	PTES	PG	60+ credits aims of diploma or Master	Web	Annual	Feb-June
Postgraduate Research Experience Survey	PRES	PG	PhD, Doctoral & Research Masters	Web	Bieannual	Mar-May
Destination of Leavers from Higher Education	DLHE	All	Received a qualification in last 6 months	Web Postal Tel	Annual	Jan & Apr
Student Experience on a Module	SEaM	All	End of a module	Web Postal	Annual	Oct-Aug
Early Course & Qualification Experience	EQE	UG	Registered with a module & new to OU	Web	Bieannual	Jan

Figure 8 Student satisfaction measurement points throughout the student journey



If OU students have already been ring fenced for another piece of research, then generally they will then be excluded from the next sample file that is prepared. Exclusions give an indication of any potential for coverage error; these are students who do not have any chance of being surveyed. There is a distinction to be made here between students who are *eligible* and ineligible. Students who are ineligible, such as those who are not registered on a module within a year cycle or who are PG/FE students when the survey is aimed at UG, are not part of the coverage error. Students who meet the eligibility criteria for the survey but who have opted out of research, participated in another survey recently or have invalid contact details for example *are* considered to be coverage error. When considering the survey objective of representing the views of the target population, coverage error is only problematic if the students who are excluded are systematically different from those who are included. Table 3 summarises the exclusions currently applied to our survey sample frames.

Table 3: OU Institutional survey exclusions

EQE	SEaM	DLHE	NSS	PTES	PRES
• Invalid e-mail • Opted out of research • Ring fenced • Included in a survey in the last year/month	• Invalid or missing e-mail address • Not registered on a module within a year cycle	• Opted out of research • Flagged as financially in debt to OU • Previously refused • No e-mail address & no UK relephone number • Sampled in last 6 months • Under 16 • Deceased	• Opted out of research • PG or FE students • Included in previous year of NSS • Incoming or exchange students • Short course or study experience less than 1 year • Dormant students • Expected end outside fieldwork • Under 16 • Deceased	• Invalid e-mail • Opted out of research • Ring fenced • Participated in a survey in the last year or month • Under 18 • No date of birth • In prison - e-mail only	• Invalid e-mail • Opted out of research • Ring fenced

2) What is known about Student Satisfaction?

The concept of measuring student satisfaction emerged in the early nineties in Australia with an instrument known as the Course Experience Questionnaire (CEQ: Ramsden, 1991). Initially this was designed to measure effective instruction using five scales:

- Good teaching;
- Clear goals and standards;
- Appropriate workload;
- Appropriate assessment and;
- Emphasis on independence.

It was later amended by replacing the final one with a 'generic skills' scale in an attempt to capture a measure of employability and then again in 2001 to include measures of physical, pastoral and social support (Ashby, Richardson, & Woodley, 2011). The survey is administered annually by the Graduate Careers Council of Australia (GCCA) to graduates from Australian institutions and the results are published as indicators of programme quality. This final version was also administered to an OU sample with adjustments to make it relevant in a distance learning context, the CEQ scales were broadly valid with the exception of 'Good Teaching' which was split into good materials and good tutoring (Ashby et al., 2011). This was used as the basis for the UK NSS development following changes to higher education quality assurance policy in early 2000.

The USA adopted a slightly different model of monitoring in 2002, choosing to focus on student engagement rather than satisfaction. This is defined in this context as 'the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes' (Hu & Kuh, 2002, p. 555). For example, the National Survey of Student Engagement (NSSE) is administered annually to first and final year students studying at US institutions and asks about five areas:

- Participation in educationally purposeful activities;
- Institutional requirements;
- Perceptions of the academic environment;
- Personal and demographic characteristics and;
- Reflections on their educational and personal growth since admission to the university. (Kuh, 2001)

Similarly to the UK, the NSSE results are made available to institutions and they are encouraged to publish key indictors in popular newspapers as comparable indictors of quality. The concept of engagement rather than satisfaction has been further developed in the UK with the introduction of a National Survey of Engagement (NSE) pilot in 2013 and 2014. The biggest difference between this survey and the NSS is that it is administered in the first and second year of undergraduate study rather than the final year. It was run in the UK with 29 volunteer institutions in 2015/16 for the first time. The OU participated in the 2014 pilot. However, the overall response rates were very low (13%) and the scales were not particularly well received by the OU students (Buckley, 2014). This was further substantiated by a pilot new version of the NSS run in 2016 with question revisions and the introduction of two new scales focusing on engagement. Analysis of the new items revealed that distance learners were less satisfied than their full time counterparts, and furthermore, they explicitly reported that these questions were not relevant for them (HEFCE, 2016). Despite these findings, the NSS will run in 2017 with the addition of the student engagement scales.

A limitation of most student survey instruments is the lack of focus on key elements of rich learning, such as interaction, assessment and feedback (Li, Marsh, & Rienties, 2016; Li, Marsh, Rienties, et al., 2016; Rienties, Li, & Marsh, 2015). Zerihun et al. (2012) argued that most student evaluation instruments are teacher-centred, focussing on what the instructor does in the learning environment, rather than what students actually do, how they engage and whether learning occurred. In addition, student satisfaction and performance tend to be reviewed as independent outcomes with little consideration of what drives each of these outcomes and in particular whether their key drivers are interrelated. Several studies have tried to close the loop in terms of linking learning satisfaction to actual learning behaviour and outcomes. Learning analytics data from VLE may be a potential treasure trove for educational researchers, such as clicking behaviour, posting in discussion forums, or watching videolectures (Rienties, Toetenel, et al., 2015; Tempelaar et al., 2015). For example, Siemens, Dawson, and Lynch (2013) suggest that in addition to VLE data, data collected as learners are undertaking authentic learning tasks need to be included in order to represent the complexity of education. However, a recent longitudinal study with 100+ learning process variables amongst 900+ learners following a blended mathematics course, including 40 different proxies of VLE behaviour, indicated that VLE behaviour only predicted 10-15% of explained variance (Tempelaar et al., 2015).

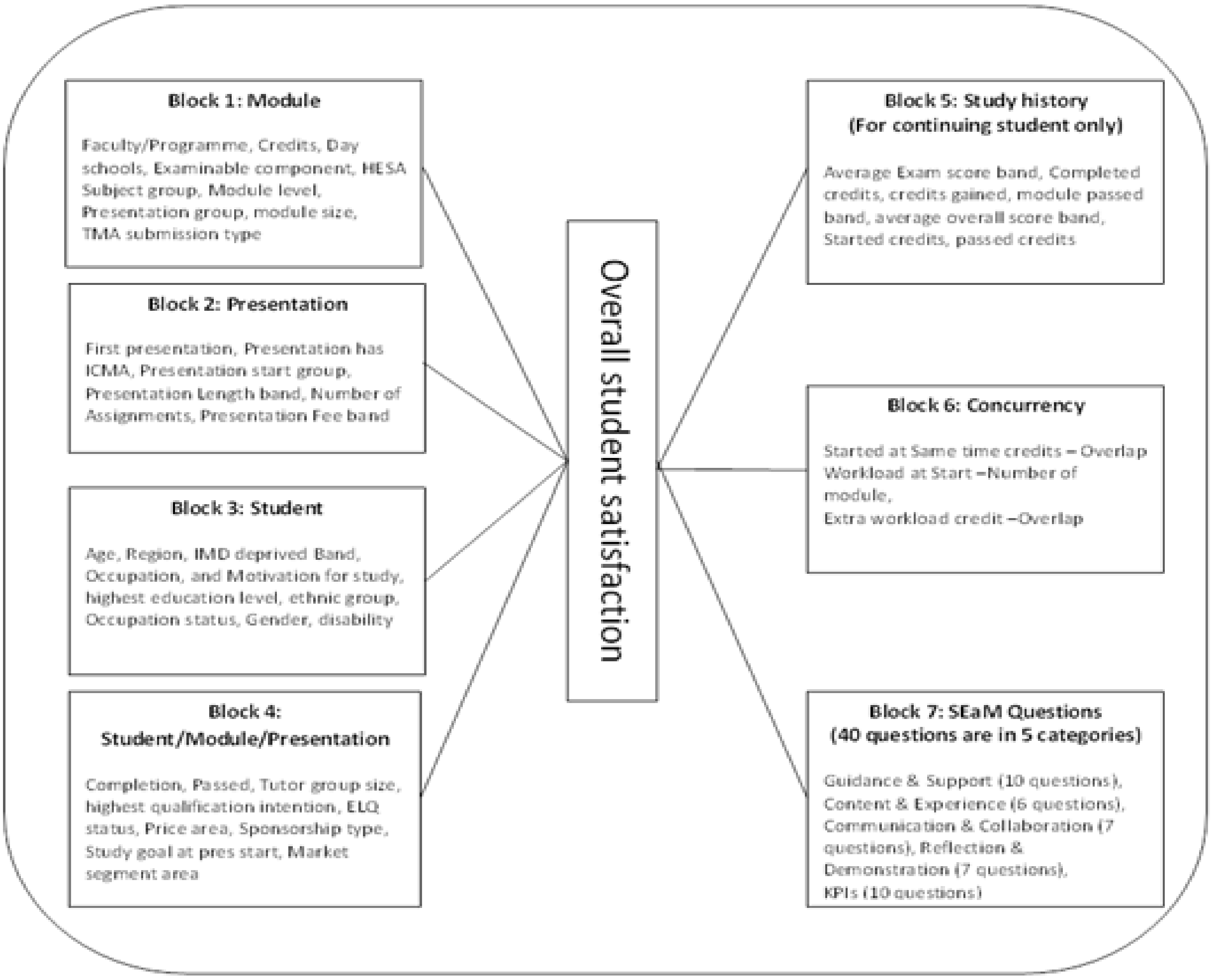
Using a structural equation model amongst 397 learners in the US following an online course, Eom, Wen, and Ashill (2006) found that learning satisfaction was a significant predictor for learning outcomes. Similarly, in an online MBA programme followed by 659 students, Marks, Sibley, and Arbaugh (2005) found that learning experience was significantly impacted by instructor-student interaction, followed by student-student interaction and student-content interaction. As mentioned before, both Arbaugh (2014) and Rienties, Toetenel, et al. (2015) found across 40+ modules that learning design and teaching support in particular influenced learners' satisfaction. Although these two studies provide substantial evidence of the usefulness of linking learning satisfaction with academic performance, a potential limitation of the first study is that it was nested primarily within an MBA context. A potential limitation of the second study was the relatively small number of modules that were included in the analysis, therefore more advanced statistical techniques to unpack disciplinary and level differences could not be conducted, which in part were addressed by Rienties and Toetenel (2016) and Nguyen et al. (2017).

Finally, it is important to recognise that there may be substantial differences in learning experiences between students who start a course for the first time, and those who have been studying at a particular institution for some time, who may have developed learning and coping mechanisms for "surviving" in online learning environments (Arbaugh, 2014; Calvert, 2014). In comparison to new students, students who have successfully completed a module may be more sensitive to (changes in) learning design choices for the next module they follow.

3) Case-studies of best-good practice and lessons learned at the OU

Although most institutions across the globe collect learning satisfaction data, few institutions have such a rich data set as the OU. The OU has consistently collected student feedback to reflect on and improve module learning design and so the student experience. The Student Experience on a Module (SEaM) institutional survey was introduced in 2012/13 combining two previous surveys using a census approach; so inviting all learners on all modules to participate. The survey consists of 40 closed (5 point Likert scale) questions and four open questions and is sent to students 2-3 weeks before the official end of a module (Ashby et al., 2011; Li, Marsh, & Rienties, 2016; Li, Marsh, Rienties, et al., 2016). Building on previous research, Li, Marsh, Rienties, et al. (2016) considered student perceptions of learning design characteristics for 401 undergraduate modules *and* individual student characteristics (n = 62,986) logistic regression modelling was used to explore the key drivers for students' learning satisfaction.

Figure 9 SEaM blocks of key constructs influencing overall satisfaction



Source: Li, Marsh, and Rienties (2016)

The purpose of this analysis was to identify which aspects of the learning experience are most associated with their overall expression of satisfaction. In particular, we were interested to explore whether satisfaction with learning design was more important than module and student characteristics, and whether new students differ in their experiences to those who already have experience with online learning. Identification of the key factors of the learning experience most closely related to satisfaction with learning design provides a clear evidence base for action.

One dependent variable was used in the studies by Li, Marsh, Rienties, et al. (2016): overall learning satisfaction (‘*Overall, I am satisfied with the quality of this module),* this variable was coded as a binary variable. Satisfied *(Definitely agree/agree)* was coded 1 and unsatisfied *(Definitely disagree/disagree/Neither agree nor disagree)* was coded 0. Given the flexibility of OU study, learners from various backgrounds can choose very different paths and approaches for studying (Ashby et al., 2011; Calvert, 2014; Richardson, 2013). An enormous amount of information (> 200 variables) related to studying at the OU was available, all of which could be potential predictors (independent variables) for overall learning satisfaction. These variables were split into seven blocks: module, presentation, learner demographics, concurrent study, study history, learner/module/presentation and SEaM questions. The selected variables for each block are presented in Figure 9. In addition to the 40 Likert response items, SEaM also include four open questions:

- What aspects of teaching materials, learning activities or assessment did you find particularly helpful to your learning?
- What aspects of teaching materials, learning activities or assessment did you find not particularly helpful to your learning? We would welcome any further suggestions or comments to consider for future editions of the module.
- Please add any further comments about your tutor. Constructive feedback is welcomed. Comments about any other tutor should be sent to your regional/national centre. Please note, your comments will be included in your tutor’s feedback report. They will be anonymous but your tutor will see any identifying information that you include.
- Do you have any other comments to add about your study experience on this module?

The results below focus on quantitative analyses of undergraduate students only, however, the results are available on request for postgraduate students. The solution was most robust when new and continuing students were considered separately, because continuing students have study history variables available for consideration. In Table 4, the results indicated that within undergraduate continuing learners, their satisfaction with *teaching materials* provided on the module is the most important driver of their overall satisfaction. The learners who were less happy with the quality of *teaching materials* (Q34) were 99% less likely to be satisfied with the overall quality of the module, compared to those who were satisfied with the teaching materials, the difference was significant ($p < .001$). Learners’ satisfaction with the *assessment on modules studied* (Q36) was the second most important driver for overall learning satisfaction. Learners who reported dissatisfaction with their assessment were 86% less likely to have positive overall learning satisfaction than those who had a much more positive experience of assessment.

Table 4 Predicting undergraduate continuing learners overall learning satisfaction: results from logistical regression analysis (in order of magnitude)

	DF	Wald x2	*P**	Odds Ratio Estimates (Definitely disagree vs. Definitely agree)
Q34 Teaching materials	4	864.465	<.001	.014
Q36 Assessment	5	224.998	<.001	.136
Q13 Qualification aim	5	114.658	<.001	.296
Q5 Integration of materials	5	89.979	<.001	.308
Q3 Advice & guidance	5	66.488	<.001	.331
Q14 Career relevance	5	38.702	<.001	.544
Q23 Tutor knowledge	5	38.167	<.001	.530
Q9 Assignment instructions	5	37.591	<.001	1.008
Q11 Assignment completion	5	36.198	<.001	.669
Q35 Workload	5	31.396	<.001	.478
Q6 Method of delivery	5	24.196	<.001	.678
Module credits (10 vs 60)	4	17.370	<.01	1.878
Module level (Level 1 vs others)	4	11.946	<.05	.854
Module exam component (Portfolio vs others)	5	11.423	<.05	.411
% of planned module life cycle (25% less vs others)	4	10.603	<.05	.726

* *Significant at the p <.05 level.*

Source: Li, Marsh, and Rienties (2016)

The results also suggested that learners were 70% less likely to have positive overall learning satisfaction if *the modules they studied did not contribute to the achievement of their wider qualification aim* (Q13). Furthermore, satisfaction with *advice and guidance provided for studies on modules* (Q3)*, the career relevance of knowledge and skills developed through studies* (Q14) were also among the top 6 important drivers of overall learning satisfaction. Other factors such as *helpfulness of tutor knowledge* (Q23)*, clear assignment instructions* (Q9) *and completion of assignment* (Q11)*, workload* (Q35) *and method of delivery of teaching materials and learning activities* (Q6) were all important drivers for overall satisfaction. This showed that learning design related factors had a significant impact on learners' overall satisfaction above and beyond student or module related characteristics. This evidence suggests that, improvements in learning design will help increase overall learning satisfaction.

As indicated at the bottom of Table 4, only a few module characteristics had a significant impact on overall learning satisfaction, such as *module level, credits and exam component* and *progress of their planned life cycle*. Learners studying relatively short 10 credit modules were twice as likely to be satisfied with their learning compared to those studying for long and intensive 60 credit modules. Learners studying at level one (i.e., year 1) were 15% less likely to be satisfied than their counterparts studying for other undergraduate levels. Learners on modules that had portfolios as an examinable component were 59% less likely to have positive overall learning satisfaction than those modules with exams and projects. Learners on newly developed modules, especially those on modules that were less than 25% of the way through the planned module life cycle, were 27% less likely to be satisfied with their overall learning experience. These variables had a significant impact on overall learning satisfaction. However, their importance was less pertinent than other learning design related variables.

Interestingly, none of the learners' characteristics (e.g., gender, age, ethnicity, prior education) had an impact on overall learning satisfaction once learning design was included in the modelling. This indicates that no matter what the OU learner's background is, their overall learning satisfaction was mainly driven by module design and learning experience. These findings imply that a well-designed module may help to increase online learners learning satisfaction, regardless of the cohort background in terms of demographics as well as their previous learning experience.

Table 5 Predicting new undergraduate overall learning satisfaction: results from logistic regression analysis (in order of magnitude)

	DF	Wald x2	P*	Odds Ratio Estimates (Definitely disagree vs. Definitely agree)
Q34 Teaching materials	4	102.629	<.001	.014
Q36 Assessment	4	46.398	<.001	.061
Q3 Advice & guidance	4	34.982	<.001	.190
Q5 Integration of materials	4	27.803	<.001	.373
Q14 Career relevance	5	20.647	<.001	.985
Q13 Qualification aim	5	17.521	<.05	.143
Age (Over 60s vs Under 21)	5	15.188	<.001	.303

** Significant at the p <.05 level.*

Source: Li, Marsh, and Rienties (2016)

Although individual student characteristics were not significantly influencing learning satisfaction amongst students who already had some experience of studying at the OU, it is important to investigate whether any individual factors influence learning satisfaction amongst new students who have just started studying for an online degree. The number of significant predictors in Table 5 was less than for continuing learners reported in Table 4, but similar patterns were found. The results indicated that a number of predictors contributed to overall learning satisfaction, the most significant predictors of overall learning satisfaction were dominated by the SEaM survey questions for new learners. The learners who were less satisfied with *Teaching materials* (Q34) were 99% significantly less likely to be satisfied with overall learning compared with their counterparts with a much more positive perception. Those who were unhappy with their *Assessment* (Q36), module contribution of their *Advice & guidance* (Q3) provided on modules they studied, or *Integration of materials* (Q5) were less likely to be satisfied with overall learning. Furthermore, *Career relevance* (Q14) and relevance of the module towards *Qualification aim* (Q13) also had an impact on learners' overall learning satisfaction.

In contrast to undergraduate continuing students, module characteristics did not have significant impact on overall learning satisfaction, as none of the variables related to module characteristics appeared to be significant predictors. The only exception of the predictors for the new learner model from the continuing learner model was *age* group, which was the only predictor related to learners' characteristics.

Table 6 Ranking of key drivers of overall learner satisfaction for new vs. continuing learners (2014 vs 2015)

	2013/2014		2014/2015	
	New	Continuing	New	Continuing
Q34 teaching materials	1	1	1	1
Q36 assessment	2	2		
Q3 advice & guidance	3	5		10
Q5 integration of materials	4	4	7	3
Q14 career relevance	5	6	6	5
Q13 qualification aim	6	3	2	2
Age (over 60s vs. under 21)	7		8	
Q23 tutor knowledge		7		11
Q9 assignment instructions		8	5	7
Q11 assignment completion		9		6
Q35 workload		10		8
Q6 method of delivery		11	3	4
Module credits (10 vs. 60)		12		12
Module level (Level 1 vs. others)		13		13
Module exam component (Portfolio vs. others)		14		
% of planned module life cycle (25% less vs. others)		15		
Q20: attendance of face-to-face tutorials			4	
Q22 tutors' online support				9

Source: Li, Marsh, Rienties, et al. (2016)

In a follow-up large scale replication study, Li, Marsh, Rienties, et al. (2016) investigated whether and how the learning satisfaction experiences of 16670 new versus 99976 continuing students were different across two academic years at the OU. Using logistical regression modelling of learner satisfaction scores of 422 undergraduate blended and online modules (including 232 learner and module learning design variables), our findings indicated that new learners indeed differed subtly in their learning and teaching experiences across two consecutive academic years, as indicated in Table 6. The minor differences in key drivers between the 2014 and 2015 cohorts also indicate that institutions need to continuously monitor and act upon changing learning needs.

In comparison to 2014 the qualification aim moved up four places for new students in 2015, being the second most important factor for learning satisfaction. Furthermore, the method of delivery, which was not a significant key driver for new students in 2014, was important for new students in 2015. In addition, face-to-face tutorials were important to new students in 2015, while continuing students in 2015 found online tutor support important. Rather surprisingly, the third most important factor for students in 2014, advice and guidance, was no longer a significant factor for new students in 2015, and was only the tenth factor for continuing students. Similarly, Q36 Assessment was no longer a key driver for new and continuing students in 2015, although Q9 Assignment instructions a key driver. In other words, in general the key drivers for learning satisfaction were similar in 2014 and 2015, but with subtle differences for new and continuing students. Overall, these predictors were closely linked to the learning design of modules, suggesting again that learning satisfaction with learning design was a better driver for overall satisfaction than the characteristics of modules, presentations and learners. Therefore, in line with previous research (Arbaugh, 2014), a better module learning design may help to improve overall learning satisfaction (Li, Marsh, & Rienties, 2016; Li, Marsh, Rienties, et al., 2016).

4) Which metrics are missing?

We have lots of examples of satisfaction measures both externally and internally, but more thought needs to be given to the salience of these metrics for distance learners in particular. We also need to think carefully about how this information is used in a strategic sense, can we be sure of the quality of the information provided? And the error associated with measuring satisfaction? Would measurement of engagement tailored to distance learning be feasible?

5) Good reads

Rienties, B., Li, N., & Marsh, V. (2015). Modeling and managing student satisfaction: use of student feedback to enhance learning experience. *Subscriber Research Series 2015-16*. Gloucester: Quality Assurance Agency.
Available at http://www.qaa.ac.uk/en/Publications/Documents/Subscriber-Research-Modelling-and-Managing-Student-Satisfaction-15.pdf

This report for the QAA provides an overview of how UK universities are making use of student surveys, and highlights the key drivers for student learning at the OU for students in academic years 2013/14

Li, N., Marsh, V., Rienties, B., & Whitelock, D. (2016). Online learning experiences of new versus continuing learners: a large scale replication study. *Assessment & Evaluation in Higher Education*.
Available at http://oro.open.ac.uk/46012/

This study provides a comparison of two years of student satisfaction at the OU, whereby significant and subtle changes in students' preferences are found, in particular to qualification aims and online support.

3. SUMMATIVE ASSESSMENT AND FEEDBACK

Assessment is a huge topic of central importance to formal education. In this chapter, we will focus narrowly on quantitative data about summative assessment. The focus is summative assessment, i.e. assessing what students have learned; the important aspect of assessment to support learning will be discussed in Chapter 4 Formative Assessment.

1) How are summative assessments measured at the OU?

This section focuses entirely on quantitative data about summative assessment. There is also a wealth of qualitative records relating to summative assessment, including the assessment material and students' responses itself, and documents produced as part of the Stage-gate process. The raw metrics for summative assessment are individual students' marks for their assessed work. Much other relevant data are also captured during the student journey. Most OU staff are familiar with the details here, but it is valuable to review them to understand some of the complexity.

For individual CMAs (Computer Marked Assessments) and iCMAs

- Individual student marks (automatically generated)
- Time submitted (late submission automatically blocked, extensions not allowed)

For individual Tutor Marked Assessments (TMAs)

- Individual student marks as originally given by Associate Lecturer (AL)
- Time submitted by student
- Time marks were returned by AL
- Details of whether an extension was applied for and granted
- Whether compulsory or optional
- Threshold, if any (thresholds can apply across more than one TMA)
- Monitoring level for this AL on this module
- Monitor comment on suitability of marks given by AL (only generated on a sample of marks)
- Cluster manager's comments on the monitor's judgement

For all continuous assessment

- The method for calculating Overall Continuous Assessment Score (OCAS) from TMA scores, including weighting and whether substitution is allowed
- Special circumstances for individual students (confidential, sent to EAB)
- Final OCAS for individual students after conflation

For end-of-module assessment

- Whether the module has an examination or EMA, or Single Component Assessment (i.e. no separate end-of-module assessment, piloted from 16J).

- Exceptional examination arrangements (recorded by SSTs, for students with and without disabilities)
- Individual students who are resitting/resubmitting
- Individual students who have been granted Discretionary Postponement or Elective Postponement
- Individual student marks as originally given by the first marker
- Individual student marks from any second marking (there may be none, a sample of second marking, or uniform double-marking)
- Tags placed on markers or questions as lenient/severe at Standardisation
- Individual student marks from any re-marking
- Adjustments made to marks through Standardisation and the EAB
- Special circumstances for individual students (confidential, sent to EAB)
- Final thresholds and grade boundaries agreed by the EAB
- Final OES for individual students after conflation

For modules overall

- Whether Assessment Banking is permitted
- Individual students who have deferred (withdrawn from one presentation and joined the next)
- Individual students who have elected to use Assessment Banking
- What forms of grade are given for each module (Pass only, Distinction/Pass, Distinction/Merit/Pass, Pass 1/2/3/4 – plus also Fail-entitled to resit/resubmit, and Fail-not entitled to resit/resubmit)
- Individual student final results (rank score) and grades

OU systems also record credit transferred by students from prior study at other institutions, which is logged when the credit is granted, before OU registration. Note that from 2016J, results will be initially agreed by a Module Result Panel before going to a cluster Examination and Assessment Board. One final set of data relevant to summative assessment that are generated and recorded are learning outcomes at module and qualification level, and in particular how those map on to assessment activities, but a full discussion of those is beyond the scope of this short overview. Direct access to almost all the assessment data listed above is available in PLANET and CIRCE MI to authorised users. In addition, for individual students, VOICE contains a complete record of their assessment results, again for those members of staff with authorisation to access it. As indicated in Chapter 2, there are also student feedback data relevant to summative assessment, specifically: SEAM Q36 (Overall I was satisfied with the assessment on this module), and NSS questions 5 (The criteria used in marking have been clear in advance) and 6 (Assessment arrangements and marking have been fair), and optional questions B10 (Teaching staff test what I have understood rather than what I have memorised and Assessment methods employed in my course require an in-depth understanding of course content). The SEaM survey is distributed before the EMA, and Cross, Whitelock, and

Mittelmeier (2015) have pointed out that student responses are therefore likely to relate more to the TMA component of the assessment than to the final assessment.

Quality assurance of marking

Several reports are generated to assist with the quality assurance. For individual tutors, the TTGAR (TMA Tutor Grade Analysis Report) shows the grades awarded compared to the mean for that module presentation, flagged as high or low, and the POTT (Profile of TMA Turnaround) report shows their mean time to return marked TMAs compared to the mean for that module presentation. At standardisation, there are a series of reports, including a scatter diagram of OES vs OCAS scores, and analyses showing score distributions by markers and by item, and comparing the current cohort's raw scores to the university scale, Senate guidelines, and previous cohorts scores.

Pass rates

Pass rates are the most widely-presented summative assessment data. Across all sources, these are given as percentages of students who passed as a fraction of those registered at the 25% fee liability point (on those modules where there is one). Different bases were used prior to 2014, so care must be taken in making comparisons with older pass rate data. Care must also be taken in comparing live pass rate data, which may not include students with results pending, and the final results calculated after conflation for AQR purposes.

Pass rate z-scores

The z-score for each module reflects how its pass rate compares to what one might have expected it to have been, given the sort of module it is. IET generates a model to predict the chance of each student passing, given their demographics, previous study, and information about the module they are studying. These are averaged to give a predicted pass rate for the module. This is compared to the actual pass rate for the module, normalised to account for the number of students on the module (we'd expect more variability on small modules), to give the z-score. A positive z-score indicates the actual pass rate is higher than the predicted rate; a negative z-score indicates that it is lower.

AQR data

Spreadsheets for each Board of Studies, showing pass rates and z-scores for each module, highlighted where they show strong or weak performance (cyan/yellow shading). Also shows the gap between completion and pass rate (i.e. the percentage who sat the exam/submitted the EMA, but failed). They also show the number of students gaining qualifications, and the time taken to gain the qualification. Produced annually to support the Annual Quality Review process (September/October).

Module Profile Tool

Excel, Word, or web page tables showing selected variables for a selected module, including TMA data (percentage submitting each TMA, scores given, etc), assessment banking, credits previously gained by students on that module, and previously passed modules. Data updated live, reports produced on demand.

Module Activity Charts

Tableau workbook showing weekly activity on a module - TMA and CMA submission rates, overlaid with students still registered and students visiting the VLE. Can be compared to another module, and broken down by new or continuing students. Updated weekly.

Pass Rate Z-scores

Spreadsheet showing predicted and actual pass rates and z-scores for all module presentations from 2012/13. Updated in line with AQR process (ca. September/October).

Five Year Trends

Spreadsheet for each Board of Studies showing pass rates for the last five academic years, also broken down by new and continuing students.

Three Year Trends

Spreadsheet for each module showing details of module (number of TMAs, etc), pass rates for the last three academic years, mean OCAS and OES, and for the latest presentation, submission rates for TMAs and CMAs. Produced around 8 weeks after the end of the presentation.

Overall OU Demographics

Spreadsheet comparing pass rates for a given academic year, broken down by module level and by Board of Studies, shown for all students, new and continuing students, and broken down by demographic groups. Produced annually for AQR process (September/October).

Module Performance View

PDF showing pass rates for the last five presentations of a selected module, compared to performance of other modules in a selected baseline (e.g. all other level 1 modules in this Faculty). Also compares demographic variables (e.g. new students, BME, financial assistance) and shows most recent SEAM data. Data based on AQR process (ca. September/October), reports produced on demand.

Qualification Profile Tool

Excel, Word or web page showing, for a selected qualification and start date, credits gained since starting the qualification, credit transferred, total credits, credits gained by level, and the number of students gaining this or other qualifications broken down by demographic variables. Data updated live, reports produced on demand.

2) What is known from the literature about summative assessment?

The literature on assessment is extensive. This brief summary is of necessity partial in both senses of the word: limited in scope, and not presenting all sides of a complex and live debate. It is interesting to note that despite the widespread agreement about the importance of assessment, student satisfaction scores for assessment are consistently lower than other aspects of the learning experience in the National Student Survey (Price, Carroll, O'Donovan, & Rust, 2011). However, the OU does appear to perform better than the HE sector and other part-time learning institutions. For example, a few years ago Buckley (2012) found that whilst 74.4% of students across the sector agreed that assessment arrangements and marking have been fair in 2011 (NSS Question 6), the comparable figure was 79.2% for part-time non-OU institutions and 88.5% for the OU.

Assessment is extremely important for students: assessment defines the de facto curriculum (Ramsden, 2003; Rowntree, 1987). What is assessed, or more precisely, what students perceive will be assessed and how, is a very powerful factor in driving their learning behaviours and learning outcomes. As Rust (2015) puts it, "[a] key foundation of the literature is that assessment is vitally important because of the influence it has on the students' approach to learning". This can be seen in quantitative terms. Over the last decade or so, there has been considerable work using modelling techniques to build predictive models of student success. Within these models, assessment scores are usually the most powerful predictive factor (Calvert, 2014; Huang & Fang, 2013; Tempelaar et al., 2015)).

This is also the case at the OU: for instance, the IET z-score model shows that summative assessment scores, and particularly continuous assessment scores, are the top predictor of student success on subsequent modules. OU Analyse (Kuzilek, Hlosta, Herrmannova, Zdrahal, & Wolff, 2015; Wolff, Zdrahal, Nikolov, & Pantucek, 2013) focuses particularly on predicting dropout *before* the first assessment scores are available, since several groups of students drop out before this stage. There is a fundamental tension between the strong desire for all students to progress, and the overriding importance of maintaining academic standards in assessment. Overall, only a small proportion of students who participate in the final exam, or submit their ECA, go on to fail the course. The failure rate for undergraduates increases from 3.1% at level 0 to 10.6% at level 3, and is 6.5% at postgraduate level[1]. In other words, if students continue as far as the final assessment, most of them are able to successfully complete the module. In other words, if students continue till the final exam, most students are able to successfully complete the module.

Concerns about validity and reliability

Studies of the reliability of marks given by human markers (e.g., Meadows & Billington, 2005; Popov & Bernhardt, 2013) yield variable results, with some studies giving alarming low rates of agreement between independent markers, and even between the same marker on the same work at different times. There is evidence that independent marking yields wider mark disparities than 'moderating', where the second marker sees the first marker's output before giving their own view (Garry, McCool, & O'Neill, 2005). There are well-established theories for testing the reliability of marking: notably, generalisability theory and Item-Response Theory. Although these are common in psychometric testing and school-level examinations in the UK (Meadows & Billington, 2005), they are not widely applied in higher education. In

[1] 2015/2016 AQR data

many contexts this may well be because the numbers of students (and therefore markers) are too small to make valid inferences: however, the OU has large numbers on many of its modules.

As well as concerns about reliability, there are concerns about validity, in that marks given do not reflect students' learning: "students may appear successful, in that they are passing the necessary assessments, while actually not having learnt the fundamental underlying concepts." (Rust, 2015). Indeed, Rust (2011) goes so far as to claim that "a first year statistics student would be failed for doing with numbers what happens in most of our assessment systems", particularly around the use of percentage numeric scores for assessment. On top of these concerns, there is considerable variability in the methods and regulations by which final degree classifications are determined at different institutions (Yorke et al., 2008), raising questions of comparability across the sector. Universities make some effort at cross-checking marks with second markers, but this is not universal, and this has contributed to a debate about the honours degree classification system. The Burgess (2007) report described the HE system as no longer fit for purpose because "[i]t cannot describe, and therefore does not do full justice to, the range of knowledge, skills, experience and attributes of a graduate in the 21st century". The report recommended the introduction of a Higher Education Achievement Report (HEAR), which gives more detail about student achievement over the entire course of their study. They are, as yet, not ubiquitous: as of 2016, 32 higher education institutions have issued a Higher Education Achievement Report (2016), but a BIS report in 2015 (J. Johnson, 2015) argued that 'this work needs greater urgency'.

Political focus appears to have shifted in the direction of US-style Grade Point Averages (GPA), with the Government arguing that it 'will provide a more granular account – through a 13 point scale developed by the sector – of student achievement - and would remove the sharpness of the cliff edge effect around the 2:1 and 2:2 border', and planning to include the use of GPAs in the TEF process (J. Johnson, 2015). In November 2013 the OU joined over a dozen other higher education provides in a pilot to test a national GPA system. Most recently, HEFCE has focused on the concept of learning gain, defined as "the 'distance travelled', or the difference between the skills, competencies, content knowledge and personal development demonstrated by students at two points in time" (McGrath, Guerin, Harte, Frearson, & Manville, 2015). There is an active programme of work in this area across 14 large-scale projects, including the ABC Learning Gains project led by the OU (Rogaten, Rienties, & Whitelock, 2016).

Marked attainment gaps across different groups

There are significant attainment gaps in terms of final assessment outcomes for students from certain groups, which are sometimes regarded as underrepresented in higher education (see throughout this Scholarly insight report). For black and ethnic minority students, Richardson (2015c) points out that not all ethnic minorities are underrepresented in higher education, but that nonetheless white students significantly outscore other ethnicities, and that this difference in assessment outcome is not fully explained by differences in entry qualifications. The attainment gap varies between institutions and between subjects, which suggests that differences in practices are partly responsible. This gap has been found clearly at the OU (e.g., Richardson, 2012). At the OU, there are significant attainment differences among students with disabilities and those without (Richardson, 2014). As illustrated in Chapter 7 Accessibility, the picture is complex: attainment differences vary across different disabilities, but the majority of disabled students are less successful than non-disabled students. The OU reports and tracks these issues through its widening participation work, including the Widening Access and Success project from CICP, which produces an annual report and a wealth of reporting data.

A shift away from examinations

Across the HE sector, and in particular in the UK, there is a shift away from end-of-module assessment by examination and towards coursework: this move is preferred by students, and tends to yield higher marks (Richardson, 2015a). This evidence, coupled with a belief that coursework assessment is more pedagogically appropriate and is likely to increase completion rates, is driving a shift away from examinations at the OU, particularly at lower levels. There is a pilot project underway exploring Single Component Assessment at level 1, where modules have no examinable component at all.

Kaye and Barrett (2016) explored differences between modules in the Faculty of Social Sciences with EMAs and those with exams. They did find slightly higher completion and pass rates for modules with EMAs, and higher scores. However, these differences were not statistically significant, and they noted that there are many other differences besides assessment type that may confound the figures. Cross et al. (2015) reported in their survey of student perceptions of feedback, assessment and revision reported that more students enjoyed doing EMAs (62.0%) and TMAs (53.6%) than an examination (25.4%) yet the proportion enjoying the revision before the exam (45.7%) was closer to that of TMAs. Cross et al. (2015) also found that whilst 75.2% and 70.9% of students felt there was enough guidance for EMAs and TMAs respectively, just 51.6% thought there was enough guidance on and during exam revision. For instance, they found that 'Satisfaction with marks received for both exams (62.7%) and EMAs (66.9%) lags behind that recorded for TMAs (80.6%)'.

3) Case-studies of best-good practice; lessons learned of what did not work

There are many projects and activities related to assessment at the OU: it is hard within a short review to illustrate the spread. The Assessment Programme is carrying out many projects exploring good practice in assessment; the OU Assessment Hub is developing an Assessment Bank of examples from the university and presents a variety of resources and links to university guidance, policy and assessment practice; the Scholarship Platform contains 78 documents related to assessment, and the projects funded by the eSTEeM centre include many concerned with assessment.

The OU has a long track record of using e-assessment, from the earliest CMAs that were returned on paper and optically scanned to generate results that were posted back to students to modern systems working with increasing sophistication. See, for instance, S. Jordan, Jordan, and Jordan (2011), which analysed the differences in difficulty between different variants of iCMA questions, as well as setting out the wider context. Many Science faculty modules moved from summative continuous assessment to a formative, thresholded model on cost grounds. An evaluation of this move by S. Jordan (2014), working with a team of sub-projects, found no evidence to support a return to the summative approach, with little difference in engagement and pass rates. S. Jordan (2014) did find that students engaged more and more deeply with formative iCMAs when they were thresholded and had a deadline. One important finding was a poor understanding among students and ALs of the assessment strategies. E-assessment is used most widely in STEM, but there are innovative assessment activities across all parts of the university. Grahame (2014) reviewed OU exam practices with a particular focus on Arts modules, finding little variation, and concluded there was considerable scope for innovation.

4) Which metrics are missing?

With the shift away from examinations, there is a need to explore more fully the available data on assessment outcomes on modules with EMAs versus those with exams, alongside developing metrics that indicate the approach students take and role they see for summative assessment. There is a need to evaluate the Single Assessment Component pilots: this evaluation is already in progress in IET. There is a need to monitor the types and uses of assessment technologies across and between modules so as to ensure consistent student experience. On modules that do have examinations, some students withdraw or do not sit the exam despite achieving good OCAS scores. There is scope for better understanding this pattern, with a view to improving advice, guidance and practice. There is a need for better evidence about the take-up and effects of assessment banking and deferrals. Over this last year Data Wrangling work (Cross, 2016) has contributed to this debate and, following a recent workshop, this work is being taken forward by the Assessment Programme with the view of providing better advice which should underpin better advice for students considering it. Finally, there may be scope for more rigorous exploration of reliability across and within markers of TMAs and examinable components.

5) Good reads

Cross, S., Whitelock, D., and Mittelmeier, J. (2015). *Student Experience of Feedback, Assessment and Revision (SEFAR) Project: Final Report.*
Available at: http://bit.ly/2hOUS06

Report setting out the results from a project exploring students' experiences around assessment, with areas where the university needs to improve highlighted.

Richardson, J. T. (2015). Coursework versus examinations in end-of-module assessment: a literature review. *Assessment & Evaluation in Higher Education*, 40(3), 439-455.
Available at: http://www.tandfonline.com/doi/abs/10.1080/02602938.2014.919628

A useful review of the literature coursework and examinations for assessment at the end of a module.

4. FORMATIVE ASSESSMENT AND FEEDBACK

1) Which metrics are currently available at the OU about formative assessment?

Key to formative assessment is good feedback. Sadler (1989) identified three conditions necessary for students to benefit from feedback in academic tasks. He argued that the student must know:

1. What good performance is (i.e. the student must possess a concept of the goal or standard being aimed for);
2. How current performance relates to good performance (for this, the student must be able to compare current and good performance);
3. How to act to close the gap between current and good performance.

Formative assessment interactions can be between tutors and learners, learners and other learners, as well as self-reflection by learners themselves; and also provided by automated systems: the later particular relevant for the OU. For example, in the module profile tool TMA's are recorded on a module, including non-assessed assignments (formative, not summative). At the OU, TMAs usually serve a dual summative and formative role. Data are updated live (Excel, Word, or web page formats), and reports produced on demand. At present, summative and formative assessments are captured under assessment learning activities in learning design mapping (see Chapter 1).

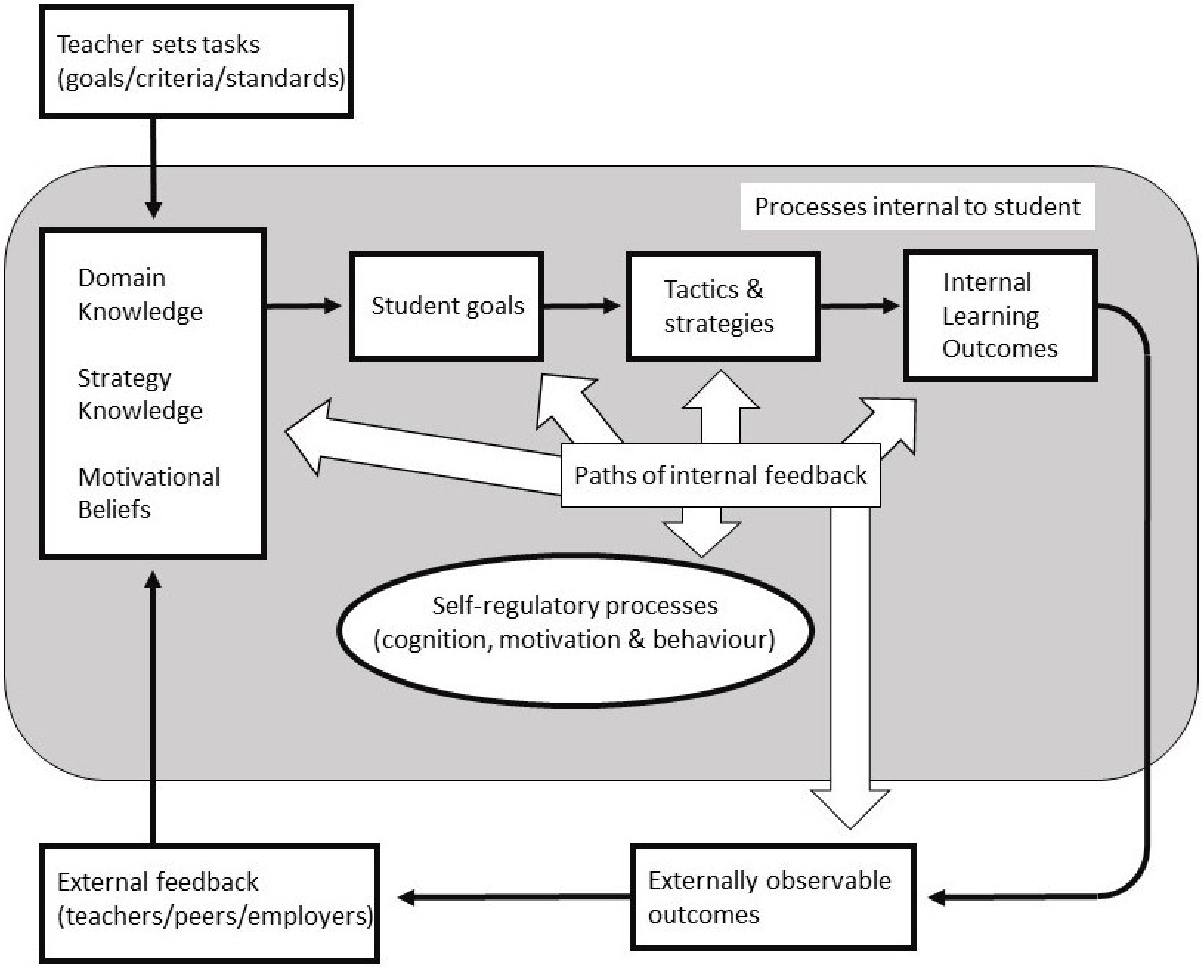
2) What is known from the literature about formative assessment and feedback?

According to Wiliam and Black (1996), formative assessment in its current sense was first used by Bloom, Hastings, and Madaus (1971, p. 117) contrasting summative assessment with "another type of evaluation which all who are involved - student, teacher, curriculum maker- would welcome because they find it so useful in helping them improve what they wish to do": this was referred to as "formative evaluation". A vast body of research has indicated that providing feedback is more important for learning than the assessment of learning (Hattie, 2009; Sharples et al., 2016). Feedback shares with the field of engineering and information theory the general assumption that information about the current state of a system can be used to change its future state. In his meta-study of 800+ meta-studies, Hattie (2009) found that the way in which students receive feedback is one of the most powerful factors associated with the enhancement of learning experiences. Hattie and Yates (2013, p. 60) considered feedback to be empowering because it enables the learner to "move forward, plot, plan, adjust rethink and exercise self-regulation".

Whitelock (2010) argued that feedback can be restrictive in nature when formative assessment's focus is that of "Assessment for Learning". She suggests that what is required in this context is "Advice for Action". This approach does not restrict itself to giving advice after a task has been completed but can also include hints given before an assessment task is taken up. Narciss and colleagues (2013; 2014) reported a randomised control trial on the automated provision of hints within short maths tasks, which also highlights the effective role of hints. Some researchers argue that giving greater responsibility to students for providing feedback has a power as great as using educator feedback (Bearman et al., 2016; Boud & Falchikov, 2006; Van Zundert, Sluijsmans, & van Merriënboer, 2010). For example, the use of peer feedback enables distance-learning educators to teach larger classes that include interactive sessions with time for reflection and personalised feedback. This feedback is mainly provided by students rather than by educators. This approach can provide significant benefits for learners when both self-reflection and peer assessment provide valuable learning experiences (Bearman et al., 2016; Van Zundert et al., 2010). Nicol et al. (2006) provided a useful list of seven principles of feedback:

1. Helps clarify what good performance is (goals, criteria, expected standards);
2. Facilitates the development of self-assessment (reflection) in learning;
3. Delivers high quality information to students about their learning;
4. Encourages teacher and peer dialogue around learning;
5. Encourages positive motivational beliefs and self-esteem;
6. Provides opportunities to close the gap between current and desired performance;
7. Provides information to teachers that can be used to help shape the teaching.

Figure 10 A model of formative assessment and feedback



Source: Nicol and Macfarlane-Dick (2006)

Building on these seven principles, Nicol et al. (2006) developed a conceptual framework how individual learners internalise assessment tasks, feedback, and guidance by teachers. The basic principles are illustrated in Figure 10, whereby teachers have to be aware that how learners internalise feedback might be different from how teachers provide external feedback. For example, in a study of six online and two blended courses, Agudo-Peregrina, Iglesias-Pradas, Conde-González, and Hernández-García (2014) found that interactions with assessment tools, interactions with peers and teachers, as well as active participation were significant predictors of academic performance in the online courses, although not in the blended ones. In contrast, in a blended course in mathematics and statistics that relied intensively on formative assessment, Tempelaar et al. (2015) found that most of the metrics that can easily be gathered from a VLE provided limited insights into student progression. However, the way students progressed in the Math and Stat formative assessments were able to explain up to 50% of the variance in student progression. Tempelaar et al. (2015) did this by carrying out a longitudinal data analysis that involved 120 variables from three different VLE systems, learning motivations, emotions and, most importantly, learners' activities during formative assessments. In particular, early formative assessment and feedback data seemed to provide teachers with effective options to help at-risk learners at a relatively early stage (Tempelaar et al., 2015). In a follow-up fine-grained study of 1,080 students using worked-out examples during continuous CBA in mathematics, Tempelaar, Rienties, and Nguyen (2017) found that students with sub-optimal learning strategies tended to us these worked-out examples at the end of the learning cycle, while students with effective metacognitive strategies used these at the beginning of the learning cycle. In other words, not only are formative assessments useful for learners in terms of just-in-time feedback and support, the data that are generated from these exercises can be useful for teachers to support learners, and where needed provide interventions.

3) Case-studies of best-good practice; lessons learned of what did not work

The OU Assessment Hub draws together a wide range of resources to support module and programme teams in the design, pedagogy and evaluation of assessment. It includes a searchable assessment 'bank' where module teams upload short evaluations of their own assessment work to share with others, and also looks outwards to the HE sector providing access to some influential resources and case studies on innovative assessment as well as highlights from assessment scholarship. The Hub is also a means of supporting Faculties' implementation of the OU's approved (2013) set of principles of assessment design and content. These cover: Developing independent learners; Qualification assessment strategy; assessment for progression in learning; tuition strategy for learning; feedback and feedforwards; peer-review and self-assessment; explicit assessment criteria.

The SEFAR project is a response to a recent finding by Whitelock and Cross (2014) that only 25% of university staff agree (and 41% disagreed) that 'there is adequate monitoring of how students experience assessment' and the fact that remains a paucity of information and insight about the end of module assessment experience (Cross et al., 2015). This study highlights the importance of understanding how formative assessment can impact on student revision and performance in examinations and EMAs (Cross, Whitelock, & Mittelmeier, 2016).

The OU has developed a tool, Open Essayist, to provide automated reflective feedback to learners on draft essays (Whitelock, Richardson, Field, Van Labeke, & Pulman, 2014). The tool presents a summary of the writing through a computer-based analysis of key sentences so that learners can compare these with the meaning they intended to convey, and adjust their writing in the light of that comparison. Adding crowd-sourcing to this type of tool with allow further automation to be achieved in the future.

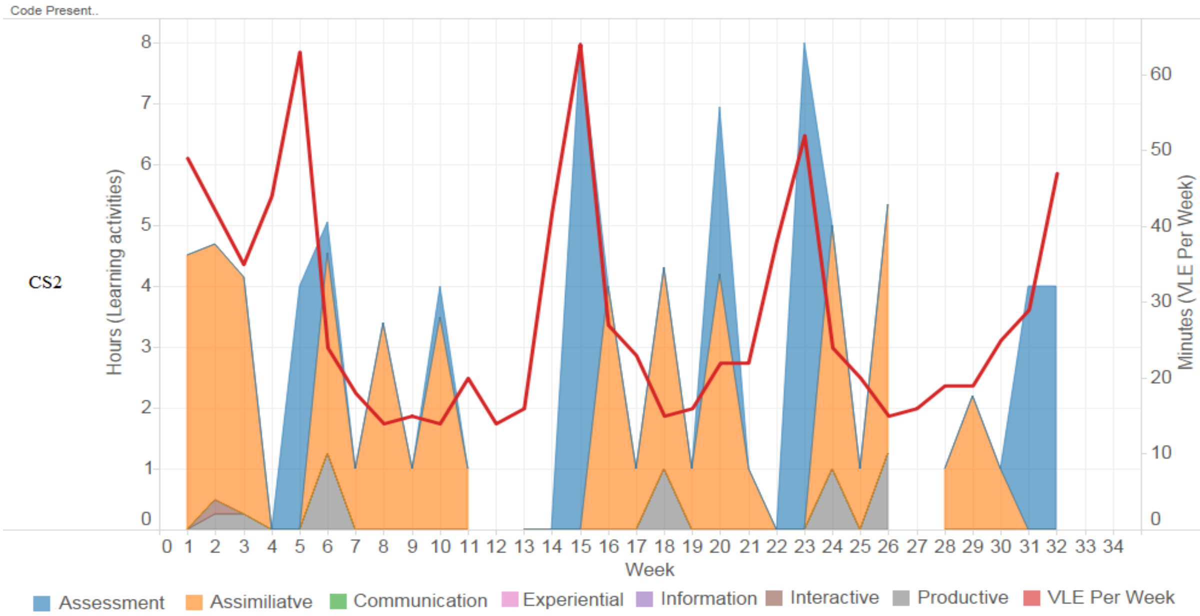
Recently, Evans et al. (2016) provided a strategic, university wide review of assessment processes as part of the NMAT project (OU): New Models of Assessment and Tuition. Evans et al. (2016) considered the specific needs of the OU as an open learning institution accepting students with no prior qualifications, 40% of whom take an Open Degree qualification. With the shift in focus in OU from module to qualification, there is a requirement to make sure that assessment strategies are "coherent and properly developmental over the whole of a qualification's study levels". This requires unlocking thinking around assessment through ownership and assessment by academic teams, supporting them to enhance their competencies and expertise as part of the institutional endeavour to better support the development of independent self-regulated learners. As also indicated in Chapter 6, we need to take into consideration the particular demographics of OU, with substantial number of students with less than A levels. Evans et al. (2016) argued that increasingly since 2012 from groups 'historically found to be less confident and prepared for distance mode HE study': students 'have little tacit knowledge and understanding of assessment literacies'. Like Cross et al. (2015), Evans et al. (2016) identified that assessments suffered from considerable inconsistencies. Furthermore, examples of exciting innovative practice were present but too frequently little known. Finally, there seemed to be an absence of transparent sharing guidelines framework. Therefore, Evans et al. (2016) encouraged the OU to develop a pan-university set of guiding "Principles for Assessment Practices".

Finally, recent work by Nguyen, Rienties, Toetenel, Ferguson, and Whitelock (Submitted) examined how formative and summative assessment approaches were configured within and between 74 OU modules, and the impact of assessment design on students' engagement, satisfaction, and pass rates. Using fixed-effect model techniques Nguyen et al. (Submitted) indicated that OU module teams designed very different assessment strategies, which significantly influenced student behaviour as measured by time spent in the VLE. Weekly analyses indicated that assessment activities were balanced with other learning activities, which suggests that educators tended to ensure a constant workload when designing assessment strategies. By controlling for heterogeneity within and between modules, learning design could explain up to 69% of the variability in students' time spent on the VLE, even though no significant relationships between assessment, satisfaction and pass rates were found.

Using weekly learning design data, follow-up fine-grained analyses by Nguyen et al. (Submitted) of six exemplars indicated that assessments were typically conducted every three weeks throughout the course, as illustrated for example in Casestudy2 (CS2) in Figure 11. A notable exception was CS4 whereby a continuous line of assessment can be seen in Figure 12 (the blue block) because students were working towards four assessments. In CS6, a vast amount of time was spent on assessment activities (see the blue blocks in Figure 13). A positive relation between assessment and time spent on VLE per week (i.e., red line) is reflected in

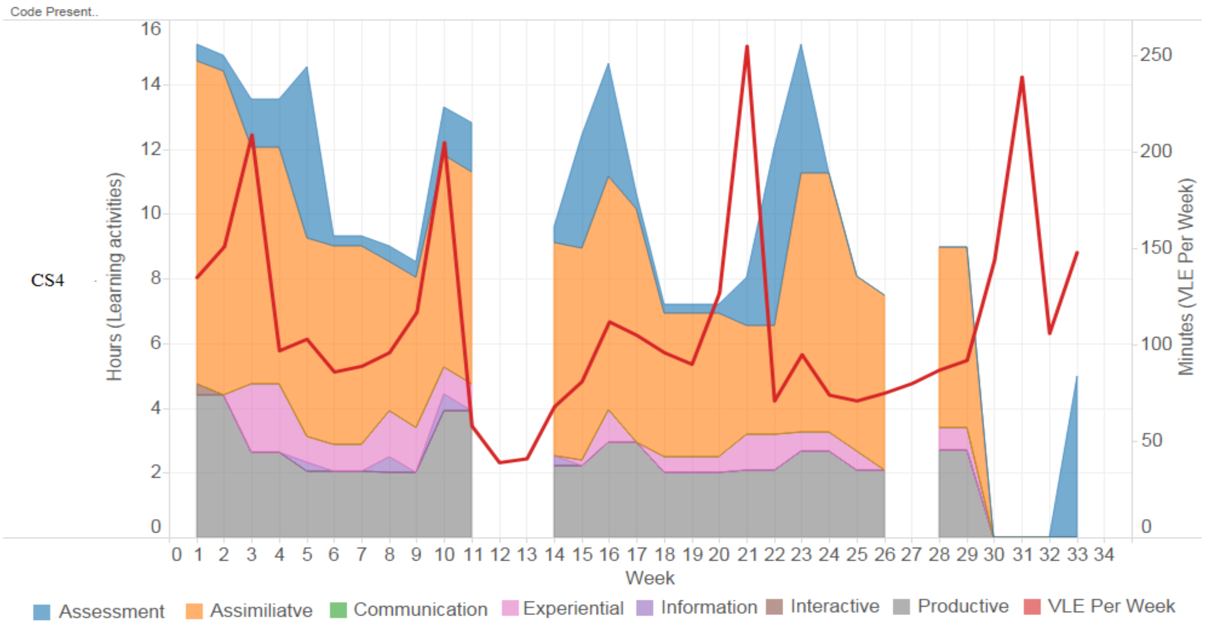
Figures 11-13, as VLE engagement mostly went up in weeks with assessment activities. The workload fluctuated considerably between assessment weeks and non-assessment weeks. In CS1, CS3, and CS5, the workload in the assessment weeks was similar to that in non-assessment weeks. However, in CS2 (see Figure 11) and CS6 (see Figure 13) students were expected to study for more time during assessment weeks than in non-assessment weeks. In other words, both the qualitative narrative, the time dedicated to assessment activities, and actual student behaviour highlight substantial differences in the way OU modules support learners and provide assessment for and of learning (Nguyen et al., Submitted).

Figure 11 Longitudinal visualization of learning design (coloured blocks) and average students' engagement (red line) in the VLE for CS2



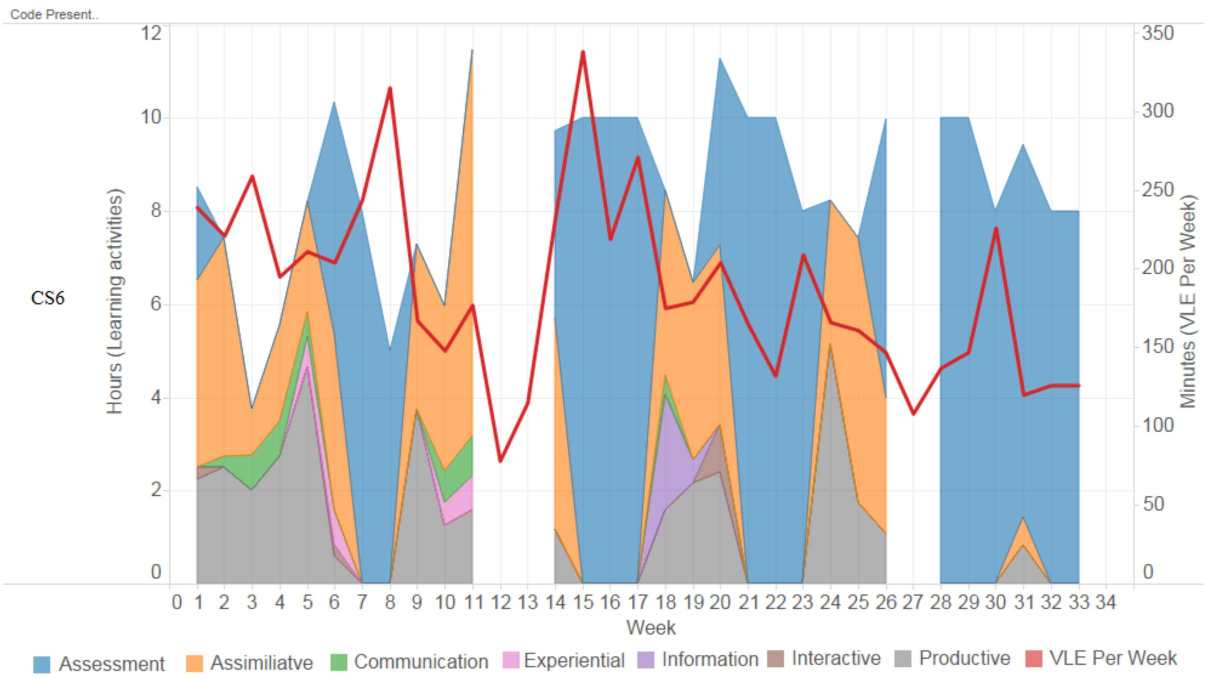
Source: Nguyen et al. (Submitted)

Figure 12 Longitudinal visualization of learning design (coloured blocks) and average students' engagement (red line) in the VLE for CS4



Source: Nguyen et al. (Submitted)

Figure 13 Longitudinal visualization of learning design (coloured blocks) and average students' engagement (red line) in the VLE for CS6



Source: Nguyen et al. (Submitted)

4) Good reads

Evans, J.; Jordan, S. and Wolfenden, F. (2016). Developing academics' assessment practices in open, distance and e-learning: an institutional change agenda. *Open Learning: The Journal of Open, Distance and e-learning*, 31(2) pp. 91–107.

Available at: http://www.tandfonline.com/doi/abs/10.1080/02680513.2016.1195547

Nicol, D. J., and Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, 31(2), 199-218.

Available at: http://www.tandfonline.com/doi/abs/10.1080/03075070600572090

Whitelock, D. and Cross, S. (2014) *Assessment: Practice and Promise,* [Internal Report]. IET, Milton Keynes.
Available at: http://bit.ly/2hDeyGs

5 INFORMAL TO FORMAL LEARNING

1. Which metrics are currently available about from informal to formal learning?

The OU uses the terms to distinguish between *formal* study for credit, and *informal* study without credit. There is value in considering not only data that relates to this interpretation but also that which relates to a more widely accepted use of the terms. By also considering other informal to formal routes including UnionLearn (Griffin, 2016) and how students have their previous achievements and experience recognised by the OU through the relevant Recognition of Prior Learning, RPL, models (Marr & James, 2015) it will allow a fuller understanding of contemporary student journeys.

This is not to take away the spotlight from our Open Media and Informal Learning unit, OMIL, and OpenLearn, as the work they do is absolutely key to the University achieving its strategic aims. The sheer numbers of individuals they reach have the potential to dramatically impact on numbers in *formal* study. If we were to learn that a significant proportion of a cohort of students on a module had arrived via a particular route through our Open Educational Resources, including those on OpenLearn, it would provide an opportunity to consider whether any changes to either the material on OpenLearn, or the teaching on the module might improve the chances of success for these students – without, of course, hindering any other student's chances. It would also enable us to announce to others taking the same OER that there is a main curriculum option that might work for them. OpenLearn also provides valuable affordances relevant to the transition to *formal* learning: the opportunity to taste OU study before committing; to explore different subject choices; of enabling students to see they are able to succeed in University study.

The usual sources of data for OU study have not directly informed us of transitions from informal to formal learning. However, anyone can register for an OpenLearn account. As a result, learners are provided with an OUCU which can then be linked with any *formal* study at the OU, should they later register for a module/qualification. Current *formal* students can use their OUCU to sign in to OpenLearn. Therefore, where *formal* students have preregistered with OpenLearn, there is a potential to cross-link with their pre-registration OpenLearn history. It should be remembered that it is of course possible to use OpenLearn without registering as these are Open Educational Resources. These usual sources are:

- Management Information (Data Warehouse) Portal
- Institutional Dashboard
- SAS Visual Analytics
- SEaM survey data

The Open Media and Informal Learning unit (OMIL), formerly the Open Media Unit, maintains records of impact by platform for OpenLearn, iTunesU and Youtube. These data include click through rates, CTR, to OU courses, and they can be found on their impact data web page (OMIL 2016). The data overwhelmingly show OpenLearn dominates in delivering click through to our *formal* offering (Law & Jelfs, 2016). The University maintains records of usage of each of the five models of Recognition of Prior Learning as detailed in Marr and James (2015). OMIL holds a range of data relating to the University's FutureLearn courses, which data on steps, comments and registrations. The OU Library currently lists 71 items for this platform, with some repeated, and the Open Research Online has 15. None so far appear to discuss students moving from studying a MOOC *informally* on FutureLearn to *formal* OU study. As noted, Open Educational Resources present some issues for those wanting to explore their effectiveness, and there is some reflection on these issues in (Pitt, Ebrahimi, McAndrew, & Coughlan, 2013).

2. What is known from the literature about informal and formal learning?

There is a rich discussion in the literature on informal and formal learning. In his work into tacit knowledge, Eraut (2000) defines formal learning as having one of the following characteristics:

- A framework that has been described
- A learning experience that has been prearranged and planned
- An allocated tutor
- Successful completion leads to the awarding of credit or a recognised qualification
- Predefined intended learning outcomes

Eraut (2000) then used the term non-formal learning to describe what is not formal, and explains why this is preferred to the term informal: which is used to describe many other aspects of an event or experience. Eraut (2000)'s interest is mainly in *non-formal learning*, which he believed accounts for the majority of what we learn. He subdivided non-formal learning into *implicit learning*, which occurs independent of any conscious thought; *reactive learning*, which emerges from a situation and of which the individual is aware; *deliberative learning*, which is the planned outcome of a non-formal learning experience. Essentially, Eraut (2000) described four forms of learning on the formal to the non-formal spectrum, as indicated in Figure 14. Eraut (2000) focussed on non-formal learning in this paper and it seems entirely likely that a focus on formal learning would reveal several sub-categories, with credit and qualifications at the very formal end and a learning experience that has been prearranged and planned at the not-so-formal end.

Figure 14 Eraut's organisation of formal and informal learning

<table>
<tr><td colspan="4">All learning</td></tr>
<tr><td rowspan="2">Formal</td><td colspan="3">Non-formal</td></tr>
<tr><td>deliberative</td><td>Reactive - on the spot</td><td>Implicit</td></tr>
</table>

Source: Eraut (2000)

The Organisation for Economic Co-operation and Development (OECD, 2016) has a strong interest in the differences between formal and other forms of learning, and distinguishes between them on its Recognition of Non-formal and Informal Learning homepage. For the OECD, formal learning is described as “always organised and structured, and has learning objectives”. It describes Informal learning as ‘never intentional’, or ‘organised’ and with no intended ‘objectives’. Non-formal learning is placed by the OECD between these two and we are told the interpretation is somewhat fluid. The OECD here describes three forms of learning on the formal<->non-formal spectrum, based upon the Werquin’s report to the OECD’s Education Policy Committee (Werquin, 2007). This report is a good overview of the use of the terms formal, non-formal and informal learning across a range of countries. Werquin (2007) proposes adding a new term, semi-formal, to give four categories to this formal<->non-formal spectrum in Table 7.

Table 7 Werquin’s definitions of formal and informal learning

The activity is planned as a learning activity:	There is intention to learn:	
	Yes: Learning is intentional	No: Learning is not intentional
Yes: The activity has [a] learning objective(s)	Formal Learning (**Type I Learning**)	Semi-formal Learning (**Type III Learning**)
No: The activity does not have [a] learning objective(s)	Non-formal Learning (**Type II Learning**)	Informal Learning (**Type IV Learning**)

Source: Werquin (2007)

The move to four categories removes the ambiguities, or fluidity, that the OECD described with the use of non-formal learning within the three category structure. However, the variables have been reduced to two: learning objectives in place?; is the learning intentional? Although Werquin (2007) argues for this simplification, it does not appear to yet be accepted by the OECD, loses some of the richness of Eraut’s approach and does not fit with the usage within the OU: as informal learning in Werquin’s model must not be intentional and must not have any learning objectives.

As described below, the OU’s strategy to increase *informal* to *formal* learning centres around moving students from OpenLearn to our standard curriculum offering. Using Eraut’s model, the OU’s journey from informal to informal learning would from a student’s perspective possibly become the journey from non-formal deliberative to formal learning. At the OU, OpenLearn materials are structured with learning outcomes and would fall into the formal category. Werquin’s model would give us a journey from formal to formal learning for both the student and institution. There is space for further clarification of what is meant by informal and formal learning and an improved description of models along the spectrum of formality between the two.

Whilst we do not need to commit to either of these models, or any other, to discuss the OU's priority to improve the journey from informal to formal learning, it is helpful to understand that we are discussing an OU specific view that may not align with the view of some outside the institution. The most significant differentiator between informal and formal learning from the perspective of the OU's strategy, is the difference between offering learning with and without credit, and everything associated with these two possibilities.

The journey from informal to formal learning at the OU

As previously noted, the OU has always been in the business of providing opportunities for students to transition from informal to formal learning: recognising that individuals are on a lifelong learning journey. Each student taking up study with the University brings their own personal learning history and reasons for study. Traditionally, there was tacit acknowledgement of some common patterns, for example, the woman who had put personal development on hold to raise her family, taking up study once her children had grown up and left home. Or the person, now retired, who wanted to take up university study to keep their mind active. Also, some younger people wanting to gain a degree to improve career prospects, after failing to succeed at school, found they could achieve this through the OU when other institutions barred their way. There have also been successful programmes and partnerships. UnionLearn is one good example: the memorandum of understanding was signed in 2006 and it continues today (Griffin, 2016).

The extent to which each individual has transitioned from informal to formal learning in the models described above would have to be argued. However, in terms of the OU use of the terms all of these would have transitioned from learning without credit to learning for HE credit. Further developments in this area include the extension of the national Social Partnerships Network (CICP, 2016). The OU is a partner in this network and has led in the development of several free Badged Open Courses and a separate website to help individuals connecting through the network to choose their most appropriate study choices, Part-time Education for Adults Returning to Learn, PEARL.

Other institutional developments to keep in mind include the recognition of prior learning (RPL). This, in essence, was considered a way of properly recognising with HE credit all forms of relevant learning that has not been awarded HE credit, against a set of criteria aligned with an HE qualification: now, some institutions including the OU bring both within their RPL offering. It would be used alongside credit-transfer schemes (Whittaker, 2010). Most institutions will offer some form of RPL, or Accreditation of Prior Learning (APL), and be able to deal with a very small number of applicants on an ad hoc basis. At the OU we have offered modules that do this effectively, and this was part of the motivation for to propose to the University a straightforward institutional framework for the Recognition of Prior Learning, to be incorporated into the Stage-gate process (Edwards & Harvey, 2012). The proposal was supported unanimously although implementation was deferred. The Senate paper (Marr & James, 2015) gives an Institutional update on RPL (using the broader definition, p.9 of the paper) and we are informed that some 130,000 students a year request RPL across the UK. As this figure does include credit transfer as one of the five modules covered by the report. A further breakdown by model is therefore necessary for considering students transitioning from informal to formal learning.

Open Educational Resources, OER, are a central element to the broadening of the platforms through which the OU maintains a strong presence, and IET hosts the OER Hub (OER Research Hub, 2014). One of the team's projects is to produce a global map of OER (Farrow, 2016). This map will enable a better understanding of the opportunities for informal learning and the possibilities for transition into *formal* OU study.

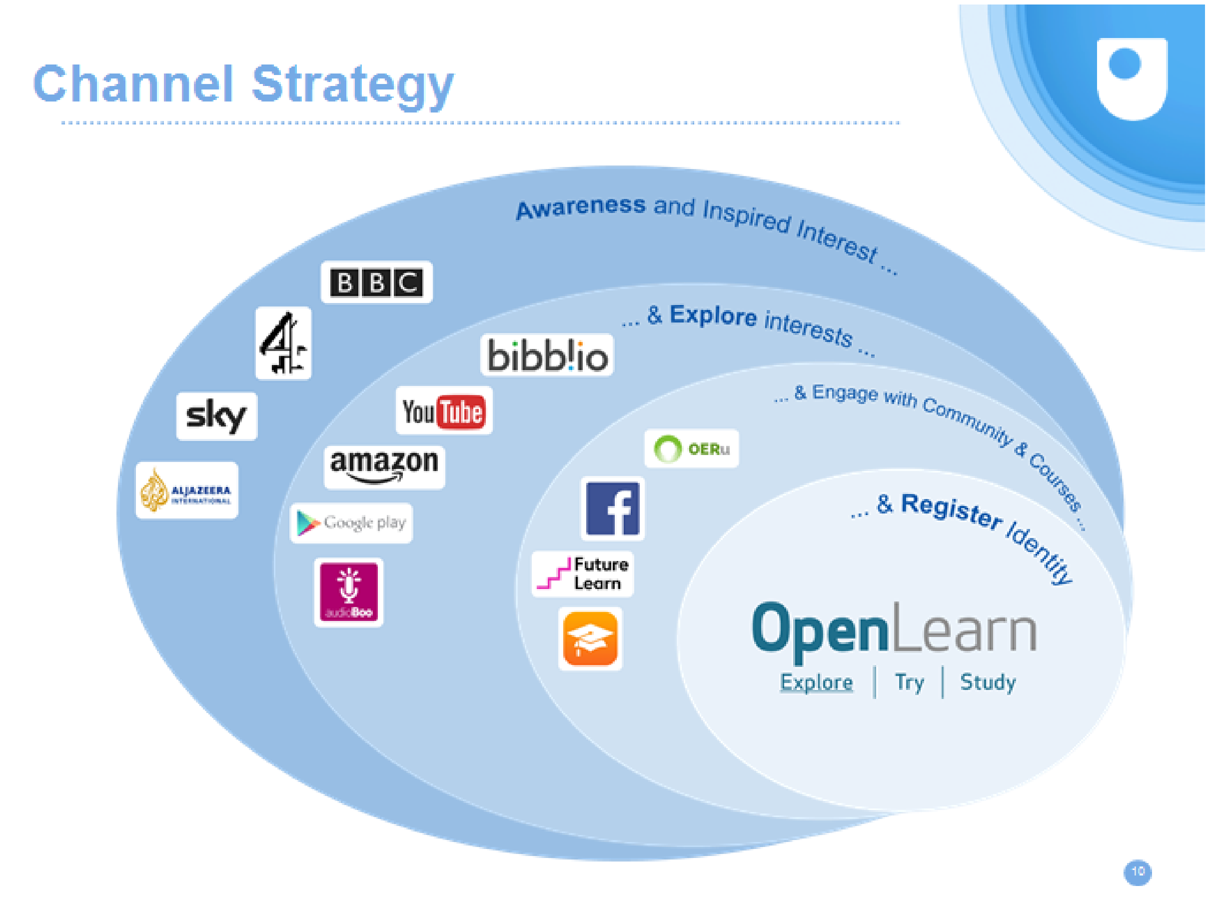
As noted, the University has a strategy for Informal to Formal Learning. Or rather, it held the strategic priority of "World leadership in delivering journeys from informal to formal learning through open media" (Open University, 2012), until this strategic plan was replaced by *Students First: Strategy for Growth* (Open University, 2016). Whilst in the current version of the text on the Students First: Strategy for Growth website there is no mention of 'informal to formal learning', the commitment to the digital platforms at the heart of the informal to formal learning objective, including OpenLearn is clear: 'Use FutureLearn, OpenLearn and other digital platforms to develop new models of learner engagement with exciting and relevant curriculum.' (Open University, 2016)

With the continued need, both financially and reputationally, to maintain and grow student numbers, it is likely the desire to facilitate students' moving from these platforms into our conventional curriculum will continue, at least into the medium term. The quotation above stresses new models of learner engagement. Badging is one emerging technology that offers the ability for the University to award recognition, if not yet credit. This could potentially be used to create a new income stream that may have the potential to become significant in the longer term and modify our thinking of the journey from informal to formal. This year's newly published Innovating Pedagogy Report (Sharples et al., 2016) describes another emerging use of technology in how blockchains could be used to validate and record achievement of credit, including exam certificates. In it we learn the first higher education institution to do this is Nicosia (Sharples et al., 2016).

In a recent study on digital badging at the OU, Law (2015) found that badges have been found to be extremely popular with our OpenLearn learners. Also, that they offer a means of offering micro-credit to our formal learners (Law, 2015). The report shows there is a lot of promise in the use of badged open courses (BOCs) as a way to engage learners and to bring them into formal study with the University, and there will be continued development of these by OMIL, at the very least over the next year or two. Some of these will be focussed on providing employability needs to be taken alongside students' formal OU study. The blending of informal and formal learning is an approach highlighted by the NMC Horizon report (L. Johnson, Adams Becker, Estrada, & Freeman, 2015), Singh (2015) and one that is encouraged by OpenLearn (Law & Jelfs, 2016).

Another way of looking at this is to consider the opportunity to gain HE credit as essentially what the OU provides to students, and teaching related income is what the OU receives for this. All offerings on other platforms can be considered to some extent a form of marketing to bring students to our *formal* offering. Historically this consisted, through our partnership with the BBC, of television broadcasts made overnight and very early morning. Students and anyone could watch and record. Over time the OU, with the BBC, has added very successful primetime television and radio programmes with website support and which click through to our online prospectus is monitored. Most recently Youtube, iTunesU, Amazon Kindle, Google Books, OpenLearn and FutureLearn have broadened our presence in mainstream media, and added dedicated online learning. Some of these offer the potential for income to the University but all of them can bring new and returning students to our *formal* curriculum. OMIL consider the various platforms within a conceptual hierarchy, shown in Figure 15. Some details of the size of the University's presence in these other platforms include: Amazon's Kindle store has 1697 free OU books (OU 2016h). Google Play similarly has very many (OU 2016i). The OU Youtube channel currently holds 'about 2,120,000' items (OU 2016j). The OU channel on iTunes U also has very many videos, audio files and transcripts (OU 2016k). Also, 'audio files are now shared on AudioBoo (www.audioboo.com); and audio and video on Bibblio (bibblio.org)' (Law & Perryman, 2015).

Figure 15 OMIL's hierarchical conceptualisation of channel strategy.



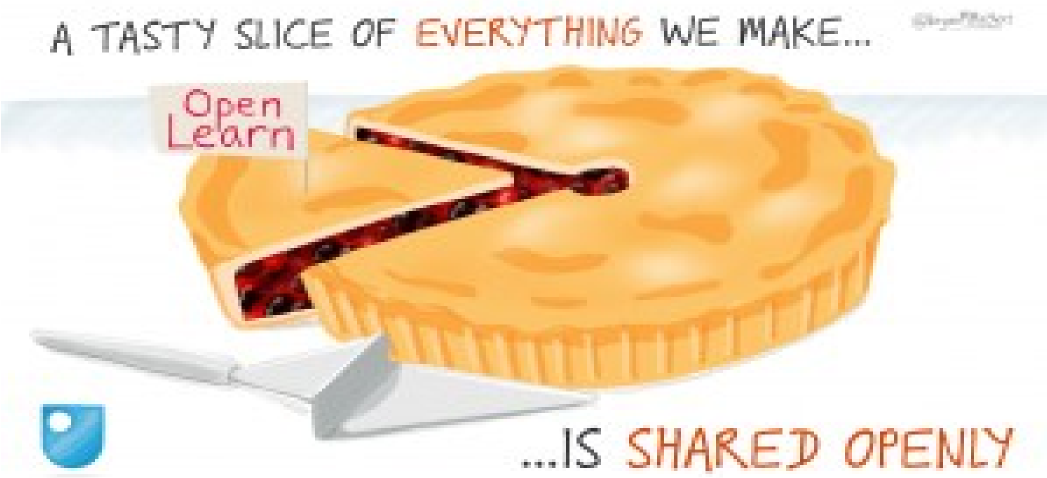
Slide reproduced from Andrew Law (2016)

3. Case-studies of best-good practice; lessons learned of what did not work

The recent Quality enhancement report MOOCs: What the OU research tells us (Ferguson, Coughlan, & Herodotou, 2016) reviews all the OU's published work on this subject. The authors distil a set of recommendations, some of which are relevant as lessons for approaching research on informal to formal learning. Scanlon, McAndrew, and O'Shea (2015) note that the barriers between formal and informal learning are diminishing and describe the use of Open Educational Resources as central to changing the way we learn to meet 21st century challenges. Ferguson and Whitelock (2014) recommend that educators should be made “aware of the range of roles and stances available to them in a MOOC, so they are able to consider how these are different from the roles of course team member and AL”.

If we are designing learning journeys from informal to formal, we should also consider the students’ learning experience and how this will change as they move from MOOCs and the other platforms into our formal curriculum. Several papers identified that those studying MOOCs are predominantly leisure learners, and to encourage retention designs could encourage students to choose to study the parts that are of interest to them (Weller, 2014), or be shorter with good linking between them to allow students to develop their own study programmes (K. Jordan, 2015). On the other hand Ferguson et al. (2015) argued we should not assume that making a course shorter will increase engagement and retention. Others suggest that developing personal learning environments, PLEs, is an effective way to negotiate the self-regulated learning, SRL, encouraged by MOOCs and open education resources, OERs, more generally (Mikroyannidis, Connolly, & Berthold, 2013).

Figure 16 Illustration to show we place a proportion of our modules on OpenLearn



Source: http://www.open.ac.uk/about/open-educational-resources/

The OMIL lead on the University’s work to deliver the strategic objectives for journeys from informal to formal learning and of developing “new models of learner engagement with exciting and relevant curriculum” (Open University, 2016). OpenLearn is the central platform and the experience over ten years has been described in Law and Jelfs (2016), whereby “the University’s systems have only recently been able to follow that journey beyond any enquiry; too early to draw any data from it regarding journey or progress”. Law and Jelfs (2016) described four affordances of OpenLearn: helping students to realise they can succeed in higher education; enabling experience of something of what it is like to study with the OU in a risk-free environment; allowing students to make better informed decisions in module choices as they study for a qualification, as 5% of each module is placed on OpenLearn; possibility of augmenting learning. The OU has proved very responsive to ensuring the success of the platform and responded quickly to introduce badged open courses, BOCs, following the research outcomes described in Law and Perryman (2015).

4. Which metrics are missing?

If we are to build a fuller picture of students' transitions from informal to formal learning we need a greater understanding of individual journeys from informal to formal learning, and as noted above, this is just beginning to become possible. Inevitably, for the richness of these journeys to be revealed individuals will also have to be enabled to tell their stories. The OU's mission to be open has always included completely open entry. Alongside this has been the recognition that some students make ill-advised choices leading to a proportion being unsuccessful in their study. The changes in funding, introduced for many OU students in 2012 and the need to register for a qualification that this entailed for students based in England exacerbated the issue. Over the years there have been many attempts to provide better information to students and tools, like Science's 'Are you ready for…' documents developed through the 90s. OER are now considered to offer a valuable new opportunity to enable students to better prepare for particular areas of study. This is the focus of the Institution's Entry Project (Mansfield, 2016) and data from this project will be useful in a consideration of *informal* to formal *learning*.

5. Good reads

Ferguson, R., Clow, D., Beale, R., Cooper, A.J., Morris, N., Bayne, S. and Woodgate, A. (2015) Moving through MOOCs: pedagogy, learning design and patterns of engagement, paper presented at *EC-TEL 2015: Tenth European Conference on Technology-Enhanced Learning*. Toledo, Spain.

Available at: http://oro.open.ac.uk/44052/1/370743_1_En_6_Chapter_Author.pdf

Law, P., & Jelfs, A. (2016). Ten years of open practice: a reflection on the impact of OpenLearn. *Open Praxis*, 8(2), 7. doi: 10.5944/openpraxis.8.2.283

Available at: http://openpraxis.org/index.php/OpenPraxis/article/view/283

Law, P., & Perryman, L.-A. (2015). Internal Responses to Informal Learning Data: Testing a Rapid Commissioning Approach. *European Journal of Open, Distance and e-Learning*, 76-84.

Available at: http://oro.open.ac.uk/44400/

6. STUDENT DEMOGRAPHICS INFLUENCING STUDENT PROGRESSION AND RETENTION

1) Which metrics are currently available?

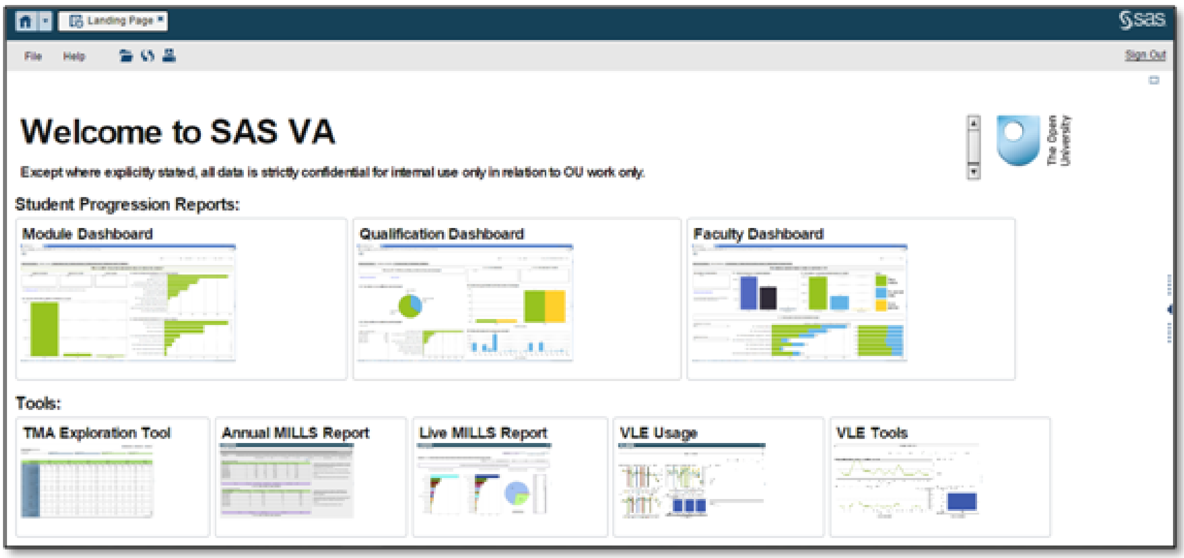
The metrics available about student demographics and retention are: the SAS Visual Analytics, OU Analyse and data in the SST website.

SAS visual analytics (SAS VA)

SAS VA provides a view of student progression and retention across the OU, Faculties, Qualifications and Modules. SAS VA can be accessed at http://bit.ly/2gUIQVu. SAS VA also tracks students' performance through qualifications. It hosts three different dashboards (see Figure 17):

1. Module dashboard gives information about qualifications on a selected module students are studying to, what other modules students are studying, students who have been withdrawn from the university, student profile (age, nation, gender, etc.), assessment results by module and qualification, number of students registered each week (retention), completion and pass rates.
2. Qualification dashboard details students' study plans per qualification, the modules they are currently studying, TMA01 results by module linked to the qualification, progression towards qualification, and students profile data
3. Faculty dashboard shows students' progression and highlights issues that can affect retention and progression. It shows which qualifications and modules are being studied by students in a faculty, the study intensity per module and qualification, and modules/qualifications with the lowest TMA01 submission rates.

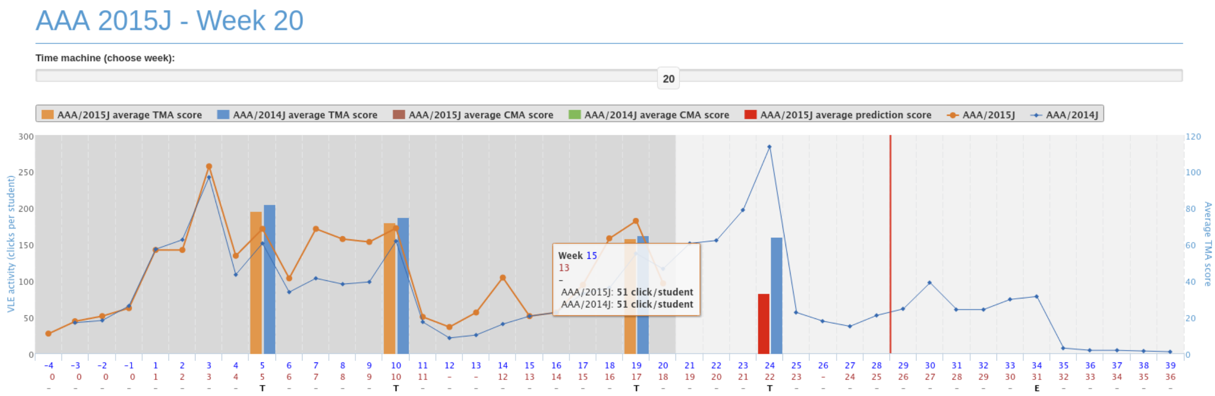
Figure 17: SAS VA dashboards



SAS VA also hosts a number of tools: a) the TMA exploration tool allows for the creation of crosstab reports (pivot tables) about TMAs, b) the Annual Mills report provides information about interventions made to learners in the period between 1st July 2015 to 20th June 2016, c)Live Mills report shows live interventions made to students per module, d) VLE usage shows the percentage of students who visited VLE per week, e) VLE tools shows percentage of students or visits per VLE tool or resource (e.g., forums, structured content). Student progression reports are provided by the Analytics team in the Learning and Teaching Centre. They are developed iteratively.

OU Analyse (OUA)
OUA is a predictive learning analytics tool that uses a range of advanced statistical and machine learning approaches to predict students at-risk and improve the retention of OU students (Hlosta, Herrmannova, Zdrahal, & Wolff, 2015; Kuzilek et al., 2015; Sharples et al., 2016; Wolff et al., 2013). At an early stage OUA identifies students who might fail to submit their next TMA. Machine learning algorithms make use of two types of data to predict students at risk: a) demographics, such as age, gender, geographic region, previous education, number of previous attempts on the module, and b) the students' interactions within the VLE hosting a module. VLE data is collected daily, representing individual actions and activity types according to the module study plan. OUA can be accessed here https://analyse.kmi.open.ac.uk/.

Figure 18: Dashboard - view of the overall course and students' VLE activity as a cohort



A list of learners who are more likely to not submit their next assessment is available in a learning analytics dashboard. The dashboard has been designed to present only the important information in order to help teachers make informed decisions about their students' performance. Figure 18 shows a section of the dashboard showing the average performance of the whole cohort of students. The current course presentation (yellow) is compared to the previous one (dark blue). The bars show the average assignment score; the lines indicate number of clicks per student in VLE activities. Figure 19 shows another section of the dashboard; at the top is the overall statistics of the current module presentation, followed by the legend and at the bottom part is the list of all students and the predictions of their performance in the next TMA. If the TMA has been already classified, the marks are in the green traffic light. Figure 20 shows information about an individual student. The target visualises similarity between the selected student (blue icon in the centre) and his/her nearest neighbours measured in terms of VLE activities (horizontal axes) and demographic parameters (vertical axes). In the Scores table the previous predictions of the student in the current presentation are shown along with the actual score if their assignment has been marked.

Figure 19: Dashboard - view of students with at-risk students flagged in red and amber

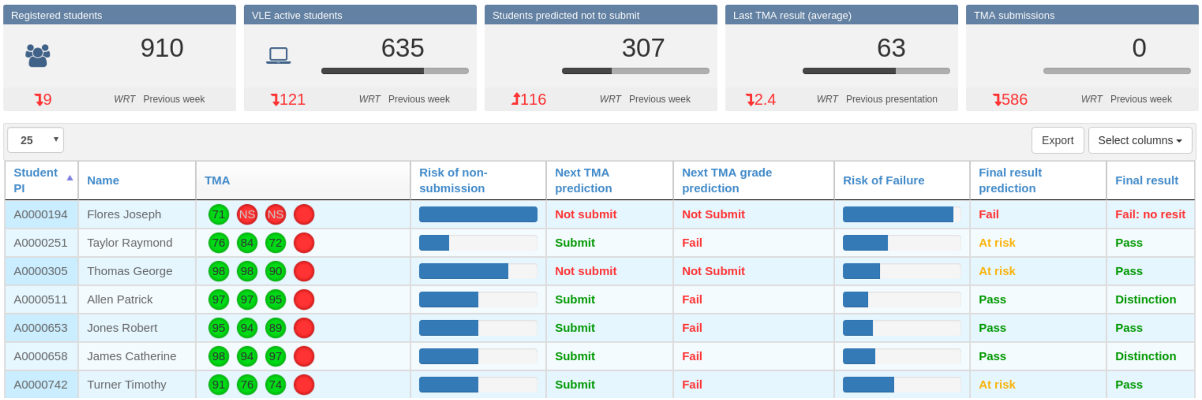
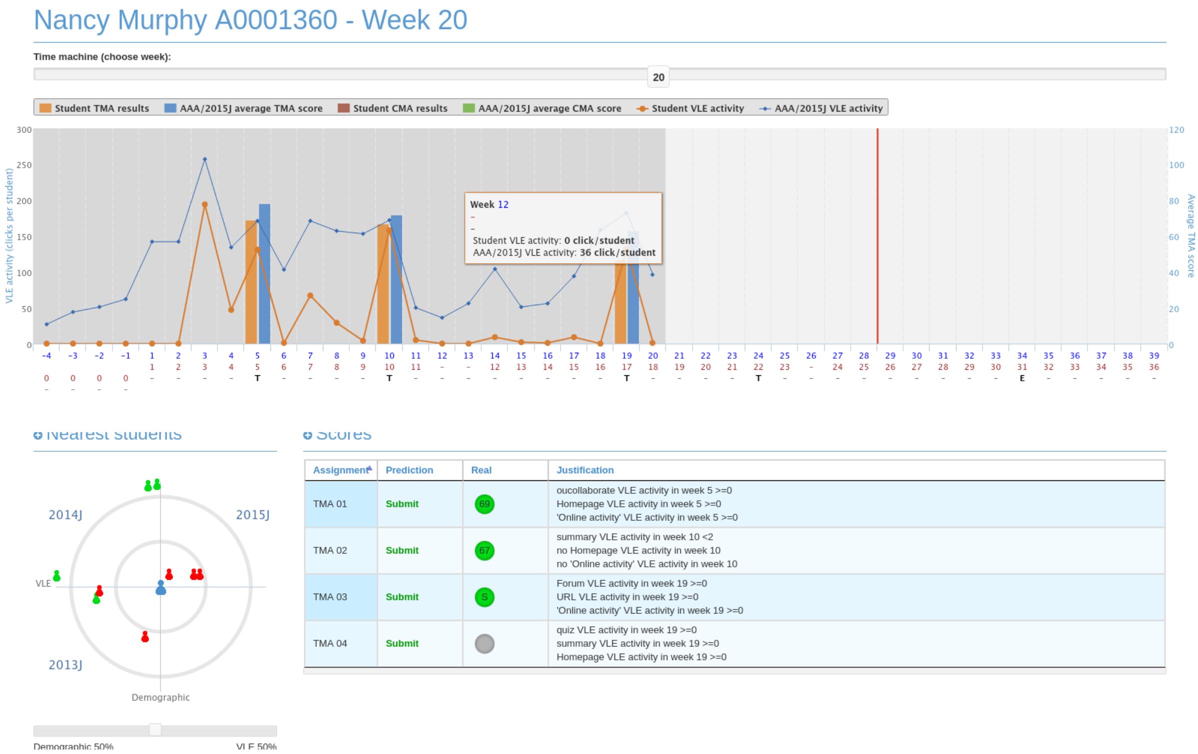


Figure 20: Dashboard - individual student view



OUAnalyse is managed by KMi. In Spring 2014 it was piloted and evaluated on two introductory university modules with about 1500 and 3000 students, respectively. By summer 2016, piloting was extended reaching more than 17 000 students across OU modules, see also the Analytics for Action (A4A) project (Rienties, Boroowa, et al., 2016; Rienties, Cross, & Zdrahal, 2016). Recently, the OU has funded the Early Alerts indicator project to evaluate the OUA with more students and modules and decide on which teachers' interventions better support students' at risk. Predictions about participating modules are available in the web dashboard application (https://analyse.kmi.open.ac.uk/)

Data in the Student Statistics and Survey Team website

The SSST website (http://intranet6.open.ac.uk/mgt-info/iet-stats/) hosts a range of information about student demographics and retention at module and qualification levels. As also indicated in Chapter 3, the SSST website provides a range of tools that give information about e.g., how many students studied a given module (see Module Profiles tool), students and ethnicity (see DIY tool) (See Figure 21).

Figure 21 Student demographics and retention in the SSST website

Module level
Module Profile tool - Detailed data on the students studying a particular module presentation.
Module Flow tool - To find out what module(s), if any, students took next.
SEAM Survey - Integration of two key surveys focussing on the student experience: The DALS and End of Module surveys.
Module Activity Charts - For an at a glance, week-by-week view of module data.
Pass rate Z-Scores - Measure whether the pass rate for a module is higher or lower than expected, given the type of module and the student cohort.
Five Year Trends - Data showing trends in pass rates over the last five years; available for individual modules within each CAU, summarised by credit points and level.
Three Year Trends - Data showing trends in registrations, completion and pass rates and latest TMA submission data for a module over the last 3 years.
OU Overall demographics - Data showing comparison of registrations, completion and pass rates for 2015/16, by demographic groups.
Module Performance View - A self-service web tool that provides a graphical representation of selected student details and survey data against a selected comparison group.
Withdrawal Survey - Data and analysis on the reasons given by students for withdrawing.
End of Module Survey - Results for module presentations ending up to Autumn 2012.
Qualification level
Qualification Profile tool - Provide a range of data on the students who started on a particular qualification, including progress data.
National Student Survey (NSS) - Student feedback on their experience of studying with The OU.
Destination of Leavers Survey (DLHE) - Analysis of what students have been doing since completing their studies.
Time to Qualification - Analyses of all OU qualifications in 2013/14 (interim), and 2007/08 - 2012/13, showing degree classification (where applicable) and length of time taken to gain qualification.
Module and Programme level
DIY tool - A very powerful online tool for comparing students on groups of modules.

2) What is known from the literature?

A vast body of research has looked at the role of student demographics at the OU. In terms of accessibility we refer to the following Chapter. For example, Myers, Phillips, Raby, and Stephens (2013) contrasted student engagement with online learning in the OU Business school by analysing a cohort of 3000 first year undergraduates. In contrast to previous expectations, Millennials had lower engagement with online elements of blended learning than expected. More active students were older students (Myers et al., 2013). Cochran, Campbell, Baker, and Leeds (2014) examined retention in online classes using previous research in face-to-face contexts. The strongest factor in determining withdrawal from an online class was found to be academic experience in that seniors are less likely to withdraw from online courses than non-seniors (freshmen). This was followed by previous withdrawals from online courses and academic performance, measured as cumulative GPA.

In a study amongst 197 distance learning students in the US, Hillstock and Havice (2014) identified the characteristics of retained first year students enrolled in non-proximal distance learning programs within public, 2-year colleges. These were: (1) non-traditional-aged White females, with a high GPA and experience with technology; (2) employed on a full-time basis and had dependent children; (3) had a high school and college GPA of above 3.0; (4) believed the institutional academic advising system was more than adequate; (5) noted that commitment to the institution and graduation were important; and (6) had access to technology. Soft skills are pertinent to academic success as emotional intelligence was found to be the most significant predictor of GPA in online learning (Berenson, Boyles, & Weaver, 2008).

Differences across modules were also reported (Arbaugh, 2014; Calvert, 2014; Cochran et al., 2014). In business, seniors, male, black or have a cumulative GPA of 3.0 or higher are less likely to withdraw from an online course. These groups are more likely to withdraw if they have done so previously. In education, students are less likely to withdraw if they are seniors or if they have need-based grants. Those more likely to withdraw are male, black or students who have loans. In health, students are more likely to withdraw from an online course if they are male or have need-based grant and are less likely to withdraw if they are older than 24. In Science/maths, students are more likely to withdraw if they have a loan or a scholarship. They are less likely to withdraw if they are seniors, male or have a cumulative GPA of 3.0 of higher (Cochran et al., 2014).

A recent review by Gazza and Hunker (2014) included 23 articles from nursing and higher education, whereby the findings show that student retention in online programs is a multidimensional issue that requires a multifaceted approach. Individual characteristics key to retention are found to be personal reasons such as life circumstances, and/or work commitments, work-study balance and workload management. Program-related factors relate to learning style and changes in career aspirations. Gazza and Hunker (2014) suggested that retention in online nursing programs can be facilitated by ensuring social presence and program and course quality, and attentiveness to individual student characteristics. Gazza and Hunker (2014) recommended to:

- Identify at-risk students and devise academic support plan
- Collaborate with withdrawing students to devise a plan for returning

- Consider the following factors when selecting students: Academic aptitude, experience in higher education, level of academic performance, previous experience with content, experience with and confidence in use of technology, internal locus of control, time management abilities, recognize impact of student employment requirements and hours, and assess student satisfaction with online learning.

In a first study on OU Analyse, Wolff et al. (2013) detailed the development of a model for predicting student failure using data from students' scores on TMAs, the average TMA score, and the number of VLE clicks in periods between submission dates of each two subsequent TMAs. It was identified that it is easier to predict failing students in the early stages of a module. VLE clicks were better for prediction than the assessment scores. VLE and TMA data combined were found to be better for prediction (Wolff et al., 2013).

In a qualitative study by Rose-Adams and Hewitt (2012) seventeen interviews with students considered as drop-outs were described. Six of them were found to be retained in formal education settings and four described their follow-up non-formal and informal learning experiences as equally important to formal learning. The remaining seven dropped out as they faced problems such as caring responsibilities, learning difficulties, pressure on finances to prioritise work over study.

In a large scale mixed-method study by Herodotou, Rienties, Boroowa, and Zdrahal (Submitted), the authors detail how predictive learning analytics (PLA) data was used in OUA to identify learners who may not complete or fail a course, typically described as being at-risk. The aim of this study was to empirically evaluate whether providing ALs with PLA data empowered them to identify and assist students at risks. A large scale mixed-methods study across 10 OU modules with 240 teachers revealed a complex picture as to whether teachers who had access to predictive data affected positively their students' performance in comparison to 613 teachers who did not have PLA data. Follow-up semi-structured interviews illuminated teachers' actual uses of the predictive data and revealed its impact on teaching practices and intervention strategies to support students at risk. The implications of this study point to the importance of using PLA data to support distance learning teaching practices and raise the need for additional large-scale studies to identify what intervention strategies should be triggered to support students effectively.

3) Which metrics are missing?

Existing studies suggest that a range of student characteristics might relate to retention in online studies such as students' age, learning and life responsibilities, financial difficulties, prior study performance, workload management, and career aspirations. The development of automated systems such as the OUA and its robust iterative evaluation across a big number of OU modules hold the potential to provide real-time predictions to the university as to which students require special attention. This gives the advantage of identifying at-risk students early on and providing support when needed to prevent a future drop-out. Furthermore, there is a clear need to identify which interventions can better support students with specific characteristics and/or at-risk of not completing their studies.

4) Good reads

Gazza, E. A., & Hunker, D. F. (2014). *Nurse Education Today Facilitating student retention in online graduate nursing education programs : A review of the literature*. *YNEDT*, *34*(7), 1125–1129. http://doi.org/10.1016/j.nedt.2014.01.010

This study provides a meta-review of how student characteristics influence online behaviour and graduation in online nursing programmes.

Available at: http://www.sciencedirect.com/science/article/pii/S0260691714000343

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M. (submitted). Using Predictive Learning Analytics to Support Just-in-time Interventions: The Teachers' Perspectives across a large-scale implementation. *Computers & Education*.

This study provides an analysis how 10 OU modules used OU Analyse, whereby some modules actively used OU Analyse and were able to increase retention.

Available at: http://bit.ly/2hjbTyq

7. ACCESSIBILITY

1) Which metrics are currently available?

Disability Markers and Profiles

Data collected on accessibility comprises a binary disability marker, a permanent disability marker (as opposed to a temporary condition), and an array of disability type categories[2]. Students are asked to disclose their disability on initial registration and then for every module. This data stays on their profile (not the module) and is their property, so students can update it themselves. Data is also recorded on VOICE and CIRCE, in a form used for HESA reporting. Once a student discloses a disability, a banner notification pops up on their Student Home requesting more information and linking to a questionnaire about needs. As part of the support process, a detailed profile is created to describe individual students and their needs. These profiles contain categories of support provided and a free text description. Most are created according to templates for categories of disability.

This process has been seen to improve the level of detail provided by students as they disclose. Alongside this is a recognition that there are students with disabilities who do not disclose, and also trends in disclosure. For example, the diagnosis of specific learning difficulties has recently gained greater traction in schools, meaning that age may be a factor in diagnosis / declaration. Attainment and student experience data can include these types on request, but tools such as Module Profile and OU Overall demographics only present the binary disability marker, and most analyses proceed from this basis.

While the process of collecting data has improved, it is important to note that there is a population of disabled students who have not, or do not, declare their disabilities. Evidence for this includes the anecdotal (e.g. students have told tutors or other staff that they do not formally declare) and in some cases, visibility of this in research data (SEaM responses and a student panel). HEFCE (2015c) data suggests that declaration of Specific Learning Difficulties in HE has increased by 38%, indicating that the impact of initiatives for diagnosis and support rather than a huge change in the population. However, we do not have a detailed analysis of the extent of these issues and it is difficult to capture them accurately. The result of potential variability in (non)disclosure is that trends in data, such as increases number of students disclosing mental health or specific learning disabilities, are difficult to interpret as either a change in population or change in rate of diagnosis/disclosure.

The disability marker is provided as a standard field in data request tools. Disability type markers are currently available through data requests (e.g. we have been working with data sets that provide these fields in SEaM responses). Overall, OU Demographics provides a Disability tab with breakdown by level and subject at 25% fee liability. Distinct from this, the SST and LSS support site gives quarterly statistics based on numbers in SSTs. Unlike the OU Demographics, these do provide data by disability type so can be used to analyse trends across

[2] These comprise Autistic Spectrum, Fatigue/Pain, Hearing, Manual Skills, Mental Health, Mobility, Other, Sight, Specific Learning Difficulties (eg_Dyslexia), Speech, Unseen.

time and programme. However, these are reported quarterly and not based on module presentation patterns.

Profile data is updated in real time. Profiles can be accessed by specific staff members and individually by students themselves via Student Home. The capacity to query the underlying database is currently being explored. There is a potential concern around a lack of version control. For example, if there were changes to the disability status of the student over time, this information may not be accurate when linked to their past studies.

Completion and Attainment

OU students declaring a disability comprise an increasing proportion of overall student registrations, from 4.18% in 2010/11, to 16.53% in 2015/16[3]. A gap between completions for disabled students when compared to other students has been persistent and large over the past three years: (-11 percentage points in 14/15 and in 13/14, -12 percentage points in 12/13). Yet this was only -6.2% in 2010/11. There are also gaps between the achievement levels of those declaring a disability and the rest of the student population. These gaps in completion and pass rate appear to be similar across levels 1-3. The gap in good passes is smaller and has been narrowing (-4 percentage points 14/15). Analysis by WAS in 2012/13 also showed variation in the completion and achievement gaps across faculties, see Table 8. An annual Widening Access and Success report, produced by colleagues in CICP, brings together data on disabled students alongside those of other Widening Participation populations. SeGA also provides links to several resources across the university on this theme. Up to date information on gaps in completion and pass rate by faculty is reported in the disability tab of OU Demographics.

Table 8: Completion and Achievement Gaps across faculties from WAS reporting

	2012/13 Disabled student registrations	Completion gap	Achievement gap
Arts	15.08%	-12.00%	-7.80%
Social Sciences	15.14%	-11.40%	-6.60%
Science	10.18%	-13.30%	-5.70%
FELS	8.80%	-12.20%	-3.30%
HSC	12.22%	-8.50%	-3.20%
MCT	11.46%	-12.40%	-3.00%
FBL	9.98%	-12.20%	-0.90%
CCIP	10.76%	-0.40%	

Source: WAS

As the population of disabled students is characterised by diversity, only a limited understanding can be gained by binary comparisons of disabled and non-disabled populations. Higher fidelity approaches, such as those used by Jelfs and Richardson (2010), Richardson (2015b) and Richardson (2009b), give insights into the perceptions and attainment of those with

[3] Widening Access and Success Annual Report 2015-16. OU Overall Demographics show 9.8% of all students still registered at 25% Fee Liability have declared a disability in 2015/16, at Level 1 it is 11.3%.

specific disabilities. For example, students declaring that they were dyslexic, deaf or hard of hearing, or had multiple disabilities, were less likely to obtain good degrees. Dyslexia is a particular area of concern with regards to distance education, where issues such the style and extent of text used in courses appear to hinder study.

The OU encourages disclosure of disabilities by students and the completion of profiles that provide information about each individual. This is an area where important strides have been made in recent years, giving us more accurate data to work with. However, further data wrangling and collaboration with colleagues is needed to harness this data fully. The Securing Greater Accessibility (SeGA) initiative (IET, 2016) brings together disability support-related staff, Accessibility Coordinators recruited in the faculties and units, and technical staff. The wealth of knowledge in this community can support data collection, interpretation, and provide leadership in actions based on insight.

Satisfaction and Student Experience

SEaM data (see also Chapter 2) has been used to identify and explore gaps in satisfaction between students declaring a disability and the rest of the student population. These appear variable according to year and source. For example, the satisfaction gap between disabled and non-disabled students reduced from 5% in 2011 to 0.6% in 2013/14. However, a 4.5% gap was identified in the same year in the NSS[4].

The analysis of open comment responses from SEaM offers opportunities to understand the perspectives and challenges faced by disabled students in greater detail. Due to the scale of these free text data sets, LTI data wranglers are currently developing an approach that combines automated techniques to identify unusually frequent keywords for those declaring different types of disability, when compared to the responses of the population that did not declare a disability and then conduct a manual categorisation and thematic analysis of the comments identified to contain these keywords. Data availability is according to standard practices of SEaM and NSS release. SEaM data can be linked to disability type markers on request.

SEaM contains a question specifically on disability and support. However, it is unclear how to interpret responses to this due to the multiple-statement nature of the question ("I have declared a disability and was able to work with the teaching materials and learning activities on this module"). Responses to this question appear to be very different to those for other SEaM questions. Given that an important part of accessibility is responsive, it would also be useful to have questions that provided insight into the support received e.g. reasonable adjustments and interactions with staff. Analysis of open comments provides insight into individual experiences and issues, but more usable quantitative data would provide a broad picture alongside this for evaluation of performance.

Requests for Reasonable Adjustments

Before or during module presentations, requests are made for individual adjustments that are considered reasonable to enable accessibility. These can make the difference between a student

[4] IET SSST, Disabled Student Satisfaction: 2013/14 Surveys with commentary from IET LTD Team.

being able to study a course or not. It is not feasible to expect that all potential needs can be addressed at the course design stage. However, changes to platform and course accessibility procedures are commonly aimed at reducing the need for requests. For example, producing alternative formats as standard and providing access to these for all students via the VLE. Given that reasonable adjustments cause challenges for students and staff, the number and type of requests is an important metric for accessibility.

As an example, a current internal research project in LTI is exploring the reasons for requests for print using data from VOICE (the university customer management system used to record interactions with students, including telephone conversations, emails and forms) and records provided by Disabled Student Services. Data received provides a student PI, course code, type of request (e.g. for a particular form of printed materials) and further details where needed. Analysis of this data in conjunction with student profiles could be used to identify trends in the need for adjustments accessibility of courses, and identify the challenges students face that cause them to make requests. Further available sources that could also be analysed to assess how well the university is performing include complaints made by disabled students, and special circumstances requests from module presentations. Data on requests for reasonable adjustments are updated in real time. Disability-related VOICE requests and the student profiles mentioned above are both regularly used and compiled by members of the Disability Support Team in Widening Access and Success Services.

Disabled Students Allowance

Sector-wide data suggests that the performance of disabled students is linked to the financial support they receive. A higher proportion of students in receipt of Disabled Student Allowance (DSA) complete a degree (83%) than those who do not receive this support but declare a disability (79%). Those with DSA are more likely to complete a degree than those who do not declare any disability (82%). A similar pattern continues into employment in graduate level jobs. The conclusion made by a report commissioned by HEFCE (2015b) is that this shows the potential to mitigate differences in attainment and employment for disabled students, given suitable forms of support.

Table 9: Students in receipt of the Disabled Student Allowance: Sector and OU figures 2010 – 2015.

Year	Full Time UG (% of all students)	Part Time UG (% of all students)	OU (% of OU students)
2014/15	82815 (7.0%)	6115 (3.4%)	2315 (2.2%)
2013/14	81455 (6.8%)	6665 (3.4%)	2645 (2.4%)
2012/13	77260 (6.5%)	7205 (3.5%)	3095 (2.8%)
2011/12	72150 (5.9%)	7475 (3.4%)	3170 (3.0%)
2010/11	62865 (5.3%)	6805 (3.0%)	2690 (2.7%)

DSA uptake has grown across the UK full time UG population, but the proportion and total of OU students receiving DSA is below average and falling for the last 4 years. This is in a context of a growing number of students declaring disabilities at the OU, as indicated in Table 9. Part time students are almost half as likely to get a DSA as their full time counterparts, but the OU is still below the sector-wide levels for PT students. Areas that have been identified as impacting on this are:

- DSA applications can take up to four months to process. Campus-based students commonly apply when they get their offer. OU students are more likely to apply after registering. They may de-prioritise completing the process, because by this point it will not be in place for the start of their studies.
- Limited resource at the point of profiling conversations with students, which then leads to less time to discuss DSA at peak registration times.
- The move from students being able to apply to the OU DSA office for DSA, to instead having to apply to Student Finance England and Student Finance Wales.
- DSA assessors are external and are not necessarily knowledgeable about distinct support likely to be required for study with the OU.
- Distance learning can remove some barriers for which DSA funds would be used, such as transport to lectures for those with mobility problems.

DSA is undergoing large-scale changes with a push towards institutions taking greater responsibility for particular forms of support. These changes make it even more important that data on the use of DSA by students and its impact is analysed such that we can respond to the changes as they take hold. Institution-level reports of students in receipt of DSA across the sector are available from HESA. The last data for 2014-15 was released in February 2016. This dataset includes comparison of PT/FT study. Within the OU, student-level DSA data is available on a SAS dataset / as a Circe table. This data is also stored as a spreadsheet in the OU DSA Office.

2) What is known from the literature about accessibility?

Several studies have identified the need to look beyond simplistic notions of accessible content, and evaluation via technical accessibility standards, towards a more holistic understanding of what is needed to overcome the barriers faced by disabled people. Using survey and interview data, Seale, Georgeson, Mamas, and Swain (2015) explored the social and cultural resources ('Digital Capital') that impact on the use of general and assistive technologies by disabled students in HE. They found that support from institutional staff, appropriate training opportunities, and attitudes towards technology, are key factors, beyond whether resources and tools are technically 'accessible'. In line with this, Cooper et al. (2012) argued that despite well-refined guidelines and metrics for web accessibility (e.g. WCAG), disabled people still face significant barriers online. These barriers remain due to a lack of understanding beyond the properties of a resource, encompassing the context of how individual disabled people interact with it. Cooper et al. (2012) argued that usage patterns (i.e. Learner Analytics) can play an important role in evaluating the quality of accessibility by identifying barriers in the context of actual interactions. Cooper et al. (2016) took this further to describe the application of OU student data to identify courses that may contain barriers for disabled students.

Given the trends and findings described in papers such as these. It is suggested that a) The evaluation of accessibility is taken to mean a holistic measurement of the ability of disabled students to study at the OU, and b) All relevant sources of data should be applied to the purpose of identifying specific areas (courses, materials, activities, support processes) where specific groups of disabled students are, or are not, able to learn on a level with their non-disabled peers.

Impact of disability on study and potential avenues for improving accessibility

As there are a range of diverse disabilities and individual circumstances, we will concentrate on two types of disabilities that are particularly pertinent to the OU and offer scope for in depth analysis: Dyslexia or other specific learning difficulties (SpLD), and Mental Health. Students with *Dyslexia or other SpLD* are less likely to pass modules or gain good grades in OU study (Richardson, 2009b, 2015b). This is highlighted as an area of particular concern and interest, as prior research (Richardson, 2009a) identified that in campus universities, this was not the case, with these students performing as well as non-disabled students. The reliance on written text in distance education is seen as a potential cause of this. New forms of online delivery and the use of assistive technology to convert text to speech are seen to aid these students. The numbers of students declaring a SpLD are large, but are not as high a proportion as found in other institutions. Further research could improve our understanding of how module design impacts on students with SpLD.

Mental health difficulties represent the largest category of declared disability at the OU, with May 2016 data recording 8194 declared students according to VOICE. It is recognised by HEFCE that the OU supports a higher proportion of students with mental health problems than other universities, that this group has grown substantially in the sector, and that those with mental health challenges are the most poorly supported in HE. The UK Government Social Mobility Advisory Group also identify this as a key area for attention. Under-disclosure has also been identified as a challenge for supporting this group, though pro-active measures have been developed recently to address this (Universities UK, 2016). Transitions to a new environment by moving away to university, and the resulting disruption to personal and professional support networks, have been identified as particularly problematic for students with mental health difficulties (Universities UK, 2016). Flexibility in terms of timing and mode of study are essential, and the OU model of study therefore has particular value to this population. Given this, it would be very useful to further examine whether OU students declaring mental health difficulties perform or experience study differently, e.g. if forms of assessment, module or qualification structure have an impact.

In terms of the OU, there are two main sources of overall statistics reporting that provide different breakdowns of the population. Table 10 reports figures from Overall OU Demographics, which provide 25% Fee Liability figures for declared disability and pass rate comparisons. The data shows increased proportions of students with declared disability at Level 1 and in Access courses, and a low proportion of postgraduate students with declared disability.

Table 10: OU Overall Demographics Disability population and pass rate gaps 2015-16

	Proportion of population declaring a disability (25% FL)	**Gap in pass rate between disability declared and no disability**
OU UG Level 1	11.3%	-10.7%
OU UG Level 2	8.6%	-11.9%
OU UG Level 3	5.4%	-12.8%
Access (CICP)	18.0%	-7.6%
OU PG	4.0%	-11.4

Disabled student numbers by category of disability is reported quarterly by the Information Office. This data is linked to programme/SST and is not based on any specific point such as 25% fee liability. It is useful to identify numbers studying with different disability types and their programme of study, as also illustrated in Table 11.

Table 11: 2016 Q4 Disabled student registrations to SSTs, by category

Category	**Total student registrations to SSTs**
Sight	1462
Hearing	1348
Mobility	4291
Manual skills	2182
Speech	452
Specific Learning difficulty (e.g. Dyslexia)	5700
Mental health	9383
Fatigue/pain	6449
Other	3006
Unseen	5341
Autism	1102

These numbers show that Mental health and Fatigue/Pain related disabilities are most commonly declared. While a large group, the numbers declaring Specific Learning Difficulties appear comparably low given the proportions reported in other HE institutions (HEFCE, 2015c). Such forms of reporting would be a useful addition to other sources, where they would reflect standard ways of reporting of student attainment / completion according to disability type, and allow issues to be identified in more fine grained ways.

Recently, Richardson (2015b) completed a review of data to explore distinctions in attainment that could be attributed to disability. He argued, based on his review of attainment data, that efforts to improve completion rates should be focused on those who are blind or partially sighted, with restricted mobility, with mental health difficulties, with 'other' disabilities, and with 'unseen' disabilities. Efforts to improve pass rates should focus in addition on those with fatigue or pain. For these students, if the course was completed and passed, their attainment matched that of non-disabled students. Students with dyslexia or other specific learning difficulties were as likely to complete, but less likely to pass or obtain good grades, as discussed previously. Richardson (2015b) also identified that some differences in attainment could also be attributed to demographic differences between populations, rather than the disability.

Online/on-screen study has potential benefits for many disabled students, such as text to speech conversion, and greater flexibility in formatting and presentation. However, the diversity of the disabled student population includes many others for whom computer-based study poses challenges or is not possible. Where modules are presented online, requests for printing of module materials as a reasonable adjustment are to be expected from these students, who include those with screen-induced migraines, fatigue, epilepsy, spinal injuries, Irlen syndrome, and arthritis. Students with dyslexia or dyspraxia typically find it difficult to sort materials and make notes with online materials, and offender learners also require adjustments. A report on this from SeGA uses data from the Alternative Formats team, Print on Demand service, and other sources to show some of the challenges to students and staff caused by moves to online study. For example, 138 requests for printed versions of online materials were made for 14J presentations, amounting to 66% of all reasonable adjustment requests, and requiring 108 hours of staff overtime to clear a backlog during October and November 2014, with delays in students getting materials vital to their study. Such analysis exemplifies forms of data that could be used to more holistically evaluate our provision for disabled and WAS students, and relate this to course provision, learning design, and actions to improve accessibility.

3) Case-studies of best-good practice; lessons learned of what did not work

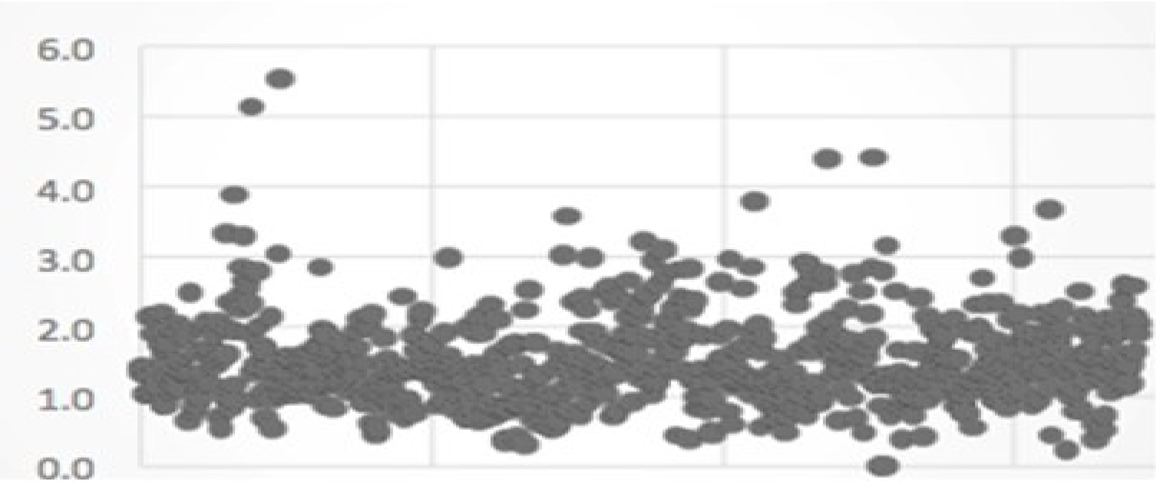
Improving Data Collection with Disabled Students

Changes to the OU approach to disclosure and to capturing details of disability have led to encouraging results. In particular, five years ago a simple 'yes' or 'no' question was used to ask registering students to make a disclosure. An average of 46% of students who declared a disability did not provide any further information (not even type of disability). Providing adequate support was then difficult. The HESA return included 7,000 disabled students whose disability was unknown. Since the introduction of a Disability Support Form this dropped to 1,600 students in the HESA return with an unknown, yet declared disability. For the rest a defined disability type is given, for 86% of those a disability profile that details their reasonable adjustment requirements has been completed. The Student Support team co-creates profiles with new students that highlight their learning needs and preferences. Profiles are regularly updated as the student progresses through their qualification.

Learner Analytics and Accessibility

Cooper et al. (2016) explored the potential of analytics to identify discrepancies in retention across OU courses for disabled students. Figure 22 explores approaches through the use of OU registration, completion, and pass data, and compared this to a method of evaluation based on coding SEaM open comment responses. Odds ratios are applied as a potential means to identify discrepancies in completion rates between disabled students on specific modules. The higher the ratio, the greater the likelihood that disability is having a significant impact on completion rates. This appears as a suitable approach to identifying modules in which there may be barriers for disabled students, however it is noted in the paper that this does not help us to identify what these barriers are, or where in a module they occur.

Figure 22: Distribution plot of odds ratios analysis (each dot represents a module presentation (distributed along the x axis in no particular order); y axis is the odds ratio.



Source: *Cooper et al. (2016)*

The qualitative analysis of SEaM data in this paper takes the approach of manually assessing whether free text comments suggest that a module had accessibility problems that could be identified through the comments. As mentioned, several data wranglers are currently investigating approaches that combine automated and manual analysis of free text content, which provides a means to summarise and understand comments across the larger body of responses from disabled students and could be applied to explore specific courses, disability types, or attainment. Critical learning pathways are suggested as a means to analyse where barriers might exist. However, such an analysis is not presented in the paper.

4) Which metrics are missing?

Cooper et al. (2016) pointed towards the need to combine data sources and analytics approaches in order to produce targeted understanding of where accessibility problems arise in OU provision. These should be applied to explore attainment, satisfaction, themes in feedback, and adjustment requests made by disabled students, in a finer-grained way than has previously been the norm. Analyses according to declared disability types are preferable to those that consider disability as a homogenous group, as the support needs and problems that will arise are often entirely different. We lack systematic metrics and reporting structures that could, for example:

- Highlight qualifications or modules with relatively good or poor performance for learners with a particular type of disability (e.g. Are particular modules a problem for those with dyslexia or visual disabilities due to their design? Do particular forms of assessment such as exams lead to poorer completion rates for those with mental health difficulties).
- Identify where the current changes to DSA provision are impacting on funding received, if this is impacting on attainment or experience, to inform how the OU should respond.
- Identify trends or anomalies in disclosure practices. For example to understand whether older students are less likely to disclose Specific Learning Difficulties due to a lack of diagnosis.

Such analyses would bring us much closer to identifying problems at a level where we can investigate and act on them. The OU records the data to achieve these analyses, but we need to combine data from different systems (that could be linked via student PI) and produce reporting processes / dashboards that really allow the identification of accessibility problems and evaluate our support for different groups of students. Such analyses could then be used to direct improvements in learning design at the module production stage, and how this integrates with support and teaching in presentation.

5) Good reads

Cooper, M., Ferguson, R., & Wolff, A. (2016). What can analytics contribute to accessibility in e-learning systems and to disabled students' learning?. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 99-103). ACM.

Available from: http://oro.open.ac.uk/45313/

As described above. A recent exploration of ways to use analytics and SEaM data to identify accessibility problems in OU modules.

Richardson, J. T. E. (2015). *Quality Enhancement Report, Academic attainment in disabled students at The OU*. IET, Milton Keynes: Open University.

Available from: http://bit.ly/2iarTTs

An in depth exploration of achievement in different categories of disability. Includes demographic variables to show how these could influence results for each category. Provides findings that suggest targeting efforts at particular groups who appear to underperform.

NEW DATA WRANGLER STRUCTURE

Many educational institutions and distance learning organizations in particular are increasingly using learner and learning data of their students to predict which students need additional support, and how business improvements can be made based upon Big Data principles (Drachsler & Greller, 2016; Ferguson, Brasher, et al., 2016; Miller & Mork, 2013; Tempelaar et al., 2015). While many organizations have recently started to use learning analytics, the OU has been using large data for nearly two decades to improve the students' experience (Ashby, 2004; Calvert, 2014). As one of the first institutions, the OU instigated a Data Wrangling initiative in 2012, whereby a dedicated academic per Faculty provided learning analytics expertise and data insight to allow Faculties to make strategic, pedagogical, and sense-making decisions.

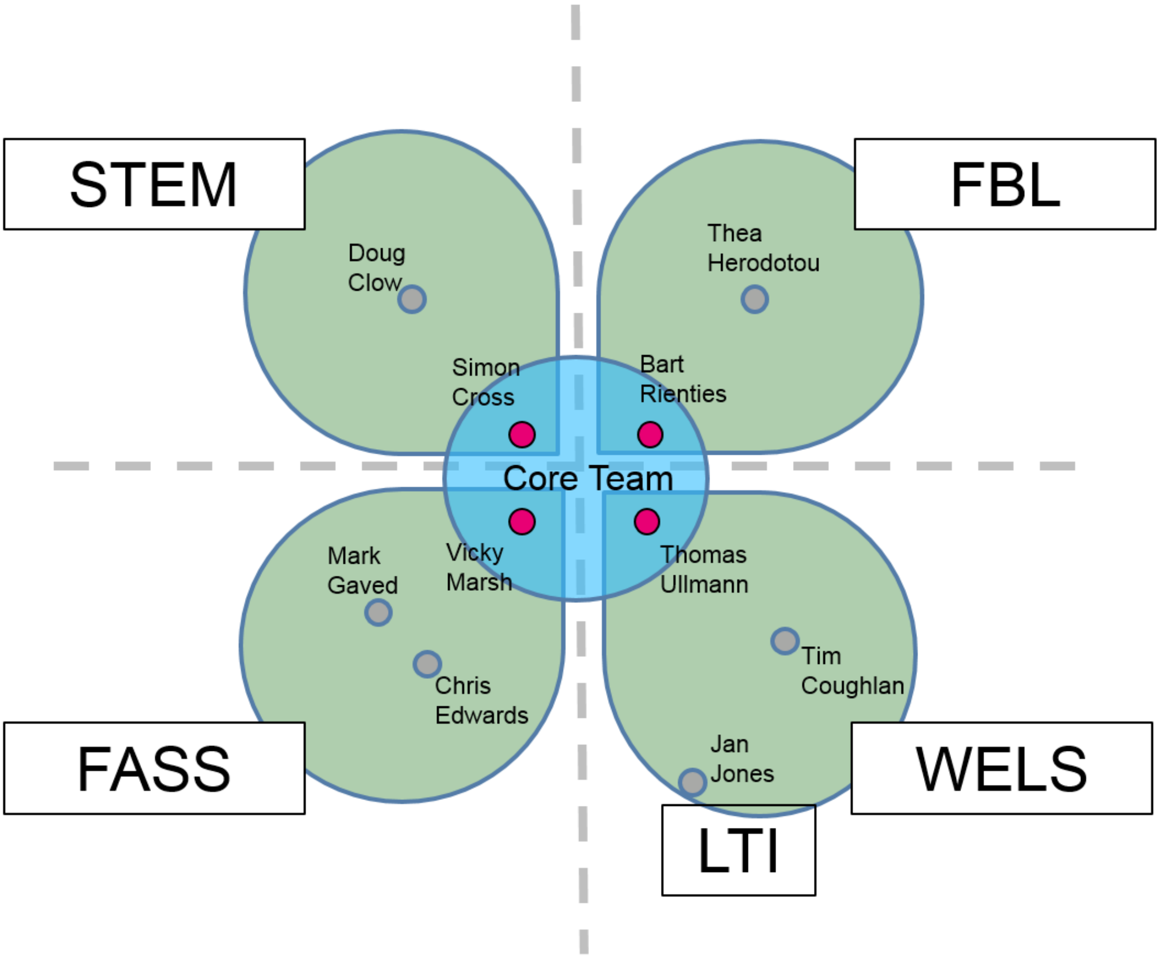
Given substantial changes within the OU over the last 18 months (e.g., new Faculty structure, real-time dashboards, two large-scale adoptions of predictive analytics approaches, increased reliance on analytics), which resemble what many organizations are pushing towards in the near future, this case-study provided an in-depth review of lessons learned of 5 years of data wrangling. Using semi-structured interviews with key stakeholders (10 senior managers/associate deans, 3 professional support staff) and ten Data Wranglers (DWs) and document analyses of previous reports, a clear mismatch was identified in terms of resources, expertise, and skills that can effectively address key needs from Faculties.

Most DWs indicated that their relationship with their respective Faculty was essential. Several DWs had regular meetings with Faculty staff and senior managers, which helped DWs to be a "translator" of the respective Faculty to get to the right question. As indicated by Buckingham Shum et al. (2013), it is essential that educational specialists are able to help senior managers and teachers to make sense of data, and to translate their questions into meaningful and insightful data analysis. At the same time as also indicated several learning analytics researchers (Buckingham Shum et al., 2013; Drachsler & Greller, 2016; Ferguson, Brasher, et al., 2016), not many people within universities have the "holy grail" of advanced statistical skills, pedagogical understanding, and ambassadorship to elicit the "right" questions from teachers and organizations, and the ability to answer these data questions in an appropriate manner.

Given the increased availability of (near) real-time data and insight within the OU, our analysis indicated a mismatch between what Faculties were expecting from DWs and what some DWs were providing. In part this was related to a wider mismatch of skills provision within the organization as a whole, while at the same time recognizing that the holy grail of skills might need to be found by putting an appropriate mix of different people together to work in teams with Faculties.

Our answer to the mismatch between skills, people, and advanced insights is to form a core team of Data Wranglers (CT), which will design and implement all core statistical analyses for all Faculties and units for both the bi-annual reporting and bespoke requests. Working towards one generic syntax linking across datasets, this will lead to standardization of practice that is robust, reliable, and most importantly replicable. In addition, the CT will work towards longitudinal rather than cross sectional perspectives which will allow DWs to provide insights of data over time, rather than at one single point in time. An obvious risk of this standardization of practice might be that the data wrangling might become a bureaucratic rather than organic process. At the same time, by ensuring the same quality and using advanced statistical techniques nested within the expertise of the CT, over time we hope to provide more coherent, robust understanding and insights of Big Data to Faculties and teachers in particular.

Figure 23 New Data wrangler structure



In Figure 23 the new structure with the Faculties is illustrated, whereby for each Faculty at least two data wranglers will be present to help to distil insight and pedagogical sense making from Big Data. Please contact us directly if you have specific questions or bespoke requests, or please contact oliver.millard@open.ac.uk

REFERENCES

Agudo-Peregrina, Á. F., Iglesias-Pradas, S., Conde-González, M. Á., & Hernández-García, Á. (2014). Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning. *Computers in Human Behavior, 31*(February), 542-550. doi: 10.1016/j.chb.2013.05.031

Arbaugh, J. B. (2014). System, scholar, or students? Which most influences online MBA course effectiveness? *Journal of Computer Assisted Learning, 30*(4), 349-362. doi: 10.1111/jcal.12048

Armellini, A., & Aiyegbayo, O. (2010). Learning design and assessment with e-tivities. *British Journal of Educational Technology, 41*(6), 922-935. doi: 10.1111/j.1467-8535.2009.01013.x

Ashby, A. (2004). Monitoring student retention in the Open University: definition, measurement, interpretation and action. *Open Learning: The Journal of Open, Distance and e-Learning, 19*(1), 65-77. doi: 10.1080/0268051042000177854

Ashby, A., Richardson, J. T. E., & Woodley, A. (2011). National student feedback surveys in distance education: an investigation at the UK Open University. *Open Learning: The Journal of Open, Distance and e-Learning, 26*(1), 5-25. doi: 10.1080/02680513.2011.538560

Bearman, M., Dawson, P., Boud, D., Bennett, S., Hall, M., & Molloy, E. (2016). Support for assessment practice: developing the Assessment Design Decisions Framework. *Teaching in Higher Education, 21*(5), 545-556. doi: 10.1080/13562517.2016.1160217

Berenson, R., Boyles, G., & Weaver, A. (2008). Emotional Intelligence as a Predictor of Success in Online Learning. *2008, 9*(2). doi: 10.19173/irrodl.v9i2.385

Bloom, B. S., Hastings, J. T., & Madaus, G. F. (1971). *Handbook on formative and summative evaluation of student learning*. New York: McGraw-Hill.

Boud, D., & Falchikov, N. (2006). Aligning assessment with long-term learning. *Assessment & Evaluation in Higher Education, 31*(4), 399-413. doi: 10.1080/02602930600679050

Buckingham Shum, S., Hawksey, M., Baker, R., Jeffery, N., Behrens, J. T., & Pea, R. (2013). Educational data scientists: a scarce breed *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 278-281). Leuven, Belgium: ACM.

Buckley, A. (2012). National Student Survey Analysis of national results for 2011. York: Higher Education Academy.

Buckley, A. (2014). UK Engagement Survey 2014: The second Pilot Year. York: Higher Education Academy.

Burgess, R. (2007). Beyond the honours degree classification: Burgess Group final report *Universities UK*. London.

Calvert, C. (2014). Developing a model and applications for probabilities of student success: a case study of predictive analytics. *Open Learning: The Journal of Open, Distance and e-Learning, 29*(2), 160-173. doi: 10.1080/02680513.2014.931805

CICP. (2016). National Networks for Collaborative Outreach (NNCO). Retrieved 19 December 2016, from http://www.open.ac.uk/cicp/main/social-partnerships/national-networks-collaborative-outreach-nnco

Cochran, J. D., Campbell, S. M., Baker, H. M., & Leeds, E. M. (2014). The Role of Student Characteristics in Predicting Retention in Online Courses. *Research in Higher Education, 55*(1), 27-48. doi: 10.1007/s11162-013-9305-8

Conole, G. (2012). *Designing for Learning in an Open World*. Dordrecht: Springer.

Cooper, M., Ferguson, R., & Wolff, A. (2016). What can analytics contribute to accessibility in e-learning systems and to disabled students' learning? *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 99-103): ACM.

Cooper, M., Sloan, D., Kelly, B., & Lewthwaite, S. (2012). *A challenge to web accessibility metrics and guidelines: putting people and processes first.* Paper presented at the Proceedings of the International Cross-Disciplinary Conference on Web Accessibility.

Cross, S. (2016). Assessment Banking in the faculty of Maths Computing and Technology: How, Who, When *IET Data Wrangling Report*. Milton Keynes: Open University.

Cross, S., Galley, R., Brasher, A., & Weller, M. (2012). Final project report of the OULDI-JISC project: challenge and change in curriculum design process, communities, visualisation and practice. York: JISC.

Cross, S., Whitelock, D., & Mittelmeier, J. (2015). Student Experience of Feedback, Assessment and Revision (SEFAR) Project: Final Report. Milton Keynes: Open University.

Cross, S., Whitelock, D., & Mittelmeier, J. (2016). *Does the Quality and Quantity of Exam Revision Impact on Student Satisfaction and Performance in the Exam Itself?: Perspectives from Undergraduate Distance Learners*. Paper presented at the 8th International Conference on Education and New Learning Technologies (EDULEARN16), Barcelona, Spain. http://oro.open.ac.uk/46937/

Daly, C., Pachler, N., Mor, Y., & Mellar, H. (2010). Exploring formative e-assessment: using case stories and design patterns. *Assessment & Evaluation in Higher Education, 35*(5), 619-636. doi: 10.1080/02602931003650052

Drachsler, H., & Greller, W. (2016). *Privacy and Analytics–it'sa DELICATE issue. A Checklist to establish trusted Learning Analytics.* Paper presented at the Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, Edinburgh.

Edwards, C., & Harvey, M. (2012). *A University Framework for the Recognition of Prior Learning, Unpublished Paper for Extended Leadership Team meeting July 2012*. Open University. Milton Keynes.

Eom, S. B., & Ashill, N. (2016). The Determinants of Students' Perceived Learning Outcomes and Satisfaction in University Online Education: An Update*. *Decision Sciences Journal of Innovative Education, 14*(2), 185-215. doi: 10.1111/dsji.12097

Eom, S. B., Wen, H. J., & Ashill, N. (2006). The Determinants of Students' Perceived Learning Outcomes and Satisfaction in University Online Education: An Empirical Investigation. *Decision Sciences Journal of Innovative Education, 4*(2), 215-235. doi: 10.1111/j.1540-4609.2006.00114.x

Eraut, M. (2000). Non-formal learning and tacit knowledge in professional work. *British Journal of Educational Psychology, 70*(1), 113-136. doi: 10.1348/000709900158001

Evans, J., Jordan, S., & Wolfenden, F. (2016). Developing academics' assessment practices in open, distance and e-learning: an institutional change agenda. *Open Learning: The Journal of Open, Distance and e-Learning, 31*(2), 91-107. doi: 10.1080/02680513.2016.1195547

Farrow, R. (2016). OER World Map. Retrieved 19 December 2016, from http://www.open.ac.uk/iet/main/research-innovation/research-projects/project-name-oer-world-map

Ferguson, R., Brasher, A., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., & Ullmann, T. D. (2016). The implications and opportunities of learning analytics for European Education Policy. In R. Vuorikari & J. Castano-Munoz (Eds.), *A European Framework for Action on Learning Analytics*. Seville: JRC Science hub.

Ferguson, R., & Buckingham Shum, S. (2012). *Social learning analytics: five approaches.* Paper presented at the Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, Vancouver, British Columbia, Canada.
Ferguson, R., Clow, D., Beale, R., Cooper, A. J., Morris, N., Bayne, S., & Woodgate, A. (2015). Moving Through MOOCS: Pedagogy, Learning Design and Patterns of Engagement. In G. Conole, T. Klobučar, C. Rensing, J. Konert, & É. Lavoué (Eds.), *Design for Teaching and Learning in a Networked World: 10th European Conference on Technology Enhanced Learning, EC-TEL 2015, Toledo, Spain, September 15-18, 2015, Proceedings* (pp. 70-84). Cham: Springer International Publishing.
Ferguson, R., Coughlan, T., & Herodotou, C. (2016). MOOCs: What the Open University research tells us. Milton Keynes: Open University.
Ferguson, R., & Whitelock, D. (2014). Taking on Different Roles: How Educators Position Themselves in MOOCs. In C. Rensing, S. de Freitas, T. Ley, & P. J. Muñoz-Merino (Eds.), *Open Learning and Teaching in Educational Communities: 9th European Conference on Technology Enhanced Learning, EC-TEL 2014, Graz, Austria, September 16-19, 2014, Proceedings* (pp. 562-563). Cham: Springer International Publishing.
Garry, J., McCool, M. A., & O'Neill, S. (2005). Are Moderators Moderate?: Testing the 'Anchoring and Adjustment'Hypothesis in the Context of Marking Politics Exams. *Politics, 25*(3), 191-200.
Gazza, E. A., & Hunker, D. F. (2014). Facilitating student retention in online graduate nursing education programs: A review of the literature. *Nurse Education Today, 34*(7), 1125-1129. doi: 10.1016/j.nedt.2014.01.010
Grahame, E. (2014). Innovating exams: new approaches to the controlled assessment of Arts modules. Final SEP project report. Milton Keynes: Open University.
Griffin, A. (2016). External Engagement - Social Partnerships & Working with Unions. Retrieved 19 December 2016, from http://intranet6.open.ac.uk/inclusion-collaborative-partnerships/main/external-engagement-social-partnerships-working-unions
Gu, Q., Schweisfurth, M., & Day, C. (2010). Learning and growing in a 'foreign' context: intercultural experiences of international students. *Compare: A Journal of Comparative and International Education, 40*(1), 7-23. doi: 10.1080/03057920903115983
Hattie, J. (2009). *Visible Learning: A synthesis of over 800 meta-analyses relating to achievement.* New York: Routledge.
Hattie, J., & Yates, G. C. (2013). *Visible learning and the science of how we learn*. New York: Routledge.
HEFCE. (2015a). Causes of Differences in Student Outcomes (pp. 17-19). London: HEFCE.
HEFCE. (2015b). Causes of differences in student outcomes. In A. Mountford-Zimdars, D. Sabri, J. Moore, J. Sanders, S. Jones, & L. Higham (Eds.). London: HEFCE.
HEFCE. (2015c). Support for Higher Education Students with Specific Learning Difficulties In J. Rodger, P. Wilson, H. Roberts, A. Roulstone, & T. Campbell (Eds.). Leeds: HEFCE.
HEFCE. (2016). Review of information about learning and teaching and the student experience. Results and analysis of for the 2016 pilot of the National Student Survey. London: HEFCE.
Heritage, M. (2007). Formative assessment: What do teachers need to know and do? *Phi Delta Kappan, 89*(2), 140-145.
Herodotou, C., Rienties, B., Boroowa, A., & Zdrahal, Z. (Submitted). Effectiveness of predictive learning analytics to support just-in-time interventions for teachers: A mixed method evaluation. *Computers & Education*.

Higher Education Achievement Report. (2016). The Higher Education Achievement Report (HEAR). Retrieved 19 December 2016, from http://www.hear.ac.uk/

Hillstock, L. G., & Havice, P. A. (2014). Exploring Characteristics of Retained First-Year Students Enrolled in Non-Proximal Distance Learning Programs. *Journal of College Student Retention: Research, Theory & Practice, 15*(4), 575-603. doi: 10.2190/CS.15.4.f

Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University. *Learning Analytics Review*, 1-16.

Hu, S., & Kuh, G. D. (2002). Being (Dis)Engaged in Educationally Purposeful Activities: The Influences of Student and Institutional Characteristics. *Research in Higher Education, 43*(5), 555-575. doi: 10.1023/a:1020114231387

Huang, S., & Fang, N. (2013). Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models. *Computers & Education, 61*, 133-145. doi: 10.1016/j.compedu.2012.08.015

IET. (2016). Securing Greater Accessibility (SeGA). Retrieved 17 December 2016, from http://www.open.ac.uk/iet/main/quality-enhancement/accessibility-and-usability/securing-greater-accessibility-sega

Jelfs, A., & Richardson, J. T. E. (2010). Perceptions of academic quality and approaches to studying among disabled and nondisabled students in distance education. *Studies in Higher Education, 35*(5), 593-607. doi: 10.1080/03075070903222666

Johnson, J. (2015). *Fulfilling our potential: Teaching Excellence, Social Mobility and Student Choice*. (Cm9141). London: Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/474266/BIS-15-623-fulfilling-our-potential-teaching-excellence-social-mobility-and-student-choice-accessible.pdf.

Johnson, L., Adams Becker, S., Estrada, V., & Freeman, A. (2015). NMC Horizon Report: 2015 Higher Education Edition. Austin, Texas: The New Media Consortium.

Jordan, K. (2015). Massive open online course completion rates revisited: Assessment, length and attrition. *2015, 16*(3). doi: 10.19173/irrodl.v16i3.2112

Jordan, S. (2014). Thresholded assessment: Does it work? Report on an eSTEeM project. Milton Keynes: Open University.

Jordan, S., Jordan, H., & Jordan, R. (2011). *Same but different, but is it fair? An analysis of the use of variants of interactive computer-marked questions*. Paper presented at the 2011 International Computer Assisted Assesment Conference, Southampton.

Kaye, H., & Barrett, J. (2016). An evaluation of the effects of exams on student retention and satisfaction. Milton Keynes: Open University.

Kember, D., & Ginns, P. (2012). *Evaluating teaching and learning*. New York: Routledge.

Koedinger, K., Booth, J. L., & Klahr, D. (2013). Instructional complexity and the science to constrain It. *Science, 342*(6161), 935-937. doi: 10.1126/science.1238056

Kuh, G. D. (2001). Assessing What Really Matters to Student Learning Inside The National Survey of Student Engagement. *Change: The Magazine of Higher Learning, 33*(3), 10-17. doi: 10.1080/00091380109601795

Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University *LACE Learning Analytics Review* (Vol. LAK15-1). Milton Keynes: Open University.

Law, P. (2015). Digital Badging at the Open University: recognition for informal learning. *Open Learning: The Journal of Open, Distance and e-Learning, 30*(3), 221-234.

Law, P., & Jelfs, A. (2016). Ten years of open practice: a reflection on the impact of OpenLearn. *Open Praxis, 8*(2), 7. doi: 10.5944/openpraxis.8.2.283

Law, P., & Perryman, L.-A. (2015). Internal Responses to Informal Learning Data: Testing a Rapid Commissioning Approach. *European Journal of Open, Distance and e-Learning*, 76-84.

Li, N., Marsh, V., & Rienties, B. (2016). Modeling and managing learner satisfaction: use of learner feedback to enhance blended and online learning experience. *Decision Sciences Journal of Innovative Education, 14*(2), 216-242. doi: 10.1111/dsji.12096

Li, N., Marsh, V., Rienties, B., & Whitelock, D. (2016). Online learning experiences of new versus continuing learners: a large scale replication study. *Assessment & Evaluation in Higher Education*. doi: 10.1080/02602938.2016.1176989

MacLean, P., & Scott, B. (2011). Competencies for learning design: A review of the literature and a proposed framework. *British Journal of Educational Technology, 42*(4), 557-572. doi: 10.1111/j.1467-8535.2010.01090.x

Mansfield, A. (2016). The Entry Project. Retrieved 16 December 2016, from http://intranet6.open.ac.uk/student-services/main/2016-newsletters/entry-project

Marks, R. B., Sibley, S. D., & Arbaugh, J. B. (2005). A Structural Equation Model of Predictors for Effective Online Learning. *Journal of Management Education, 29*(4), 531-563. doi: 10.1177/1052562904271199

Marr, L., & James, A. (2015). Recognition of Prior Learning Policy, Senate paper. Milton Keynes: Open University.

Marsh, H. W. (1982). SEEQ: a reliable, valid, and useful instrument for collecting students' evaluations of university teaching. *British Journal of Educational Psychology, 52*, 77-95.

McGrath, C. H., Guerin, B., Harte, E., Frearson, M., & Manville, C. (2015). Learning gain in higher education. Cambridge: HEFCE/RAND.

Meadows, M., & Billington, L. (2005). A review of the literature on marking reliability. London: National Assessment Agency.

Mikroyannidis, A., Connolly, T., & Berthold, M. (2013). Self Regulated Learning. Milton Keynes: Open University.

Miller, H. G., & Mork, P. (2013). From Data to Decisions: A Value Chain for Big Data. *IT Professional, 15*(1), 57-59. doi: 10.1109/MITP.2013.11

Moskal, A. C. M., Stein, S. J., & Golding, C. (2015). Can you increase teacher engagement with evaluation simply by improving the evaluation system? *Assessment & Evaluation in Higher Education, 41*(2), 286-300. doi: 10.1080/02602938.2015.1007838

Myers, F., Phillips, M., Raby, P., & Stephens , C. (2013). Engaging large groups of individual learners through an online environment – an emerging i-Learner generation? In E. Doyle, P. Buckley, & C. Carroll (Eds.), *Innovative Business School Teaching*. Abingdon: Routledge.

Narciss, S. (2013). Designing and evaluating tutoring Feedback Strategies for Digital Learning. *Digital Education Review*(23), 7-26.

Narciss, S., Sosnovsky, S., Schnaubert, L., Andrès, E., Eichelmann, A., Goguadze, G., & Melis, E. (2014). Exploring feedback and student characteristics relevant for personalizing feedback strategies. *Computers & Education, 71*, 56-76. doi: 10.1016/j.compedu.2013.09.011

Nguyen, Q., Rienties, B., & Toetenel, L. (2017). *Unravelling the dynamics of instructional practice: A longitudinal study on learning design and VLE activities.* Paper presented at the LAK 2017, Vancouver, Canada.

Nguyen, Q., Rienties, B., Toetenel, L., Ferguson, F., & Whitelock, D. (Submitted). The impact of assessment design on student behaviour, satisfaction and performance. *Computers in Human Behavior*.

Nicol, D., & Macfarlane-Dick, D. (2006). Formative assessment and selfregulated learning: a model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199-218. doi: 10.1080/03075070600572090

OECD. (2016). Recognition of non-formal and informal learning. Retrieved 19 December 2016, from http://www.oecd.org/edu/skills-beyond-school/recognitionofnon-formalandinformallearning-home.htm

OER Research Hub. (2014). OER Impact Map. Retrieved 19 December 2016, from http://oerresearchhub.org/

Onwuegbuzie, A. J., Witcher, A. E., Collins, K. M. T., Filer, J. D., Wiedmaier, C. D., & Moore, C. W. (2007). Students' perceptions of characteristics of effective college teachers: a validity study of a teaching evaluation form using a mixed-methods analysis. *American Educational Research Journal, 44*(1), 113-160. doi: 10.3102/0002831206298169

Open University. (2012). The Open University Strategic Plan 2012-17: Securing the Mission. Milton Keynes: Open University.

Open University. (2016). The Strategic Plan. Retrieved 19 December 2016, from https://intranet7.open.ac.uk/collaboration/strategic-plan/SitePages/Home.aspx

Palincsar, A. S. (2005). 12 Social constructivist perspectives on teaching and learning. *An introduction to Vygotsky*, 285.

Pitt, R., Ebrahimi, N., McAndrew, P., & Coughlan, T. (2013). Assessing OER impact across organisations and learners: experiences from the Bridge to Success project. *Journal of Interactive Media in Education, 2013*(3). doi: 10.5334/2013-17

Popov, S. V., & Bernhardt, D. A. N. (2013). University competition, grading standards, and grade inflation. *Economic Inquiry, 51*(3), 1764-1778. doi: 10.1111/j.1465-7295.2012.00491.x

Price, M., Carroll, J., O'Donovan, B., & Rust, C. (2011). If I was going there I wouldn't start from here: a critical commentary on current assessment practice. *Assessment & Evaluation in Higher Education, 36*(4), 479-492. doi: 10.1080/02602930903512883

Quality Assurance Agency. (2000). Code of practice for the assurance of academic quality and standards of higher education. Section 6: Assessment of Students. London: QAA.

Ramsden, P. (1991). A performance indicator of teaching quality in higher education: The Course Experience Questionnaire. *Studies in Higher Education, 16*(2), 129-150. doi: 10.1080/03075079112331382944

Ramsden, P. (2003). *Learning to teach in higher education* (2 ed.). London: Routledge.

Ras, E., Whitelock, D., & Kalz, M. (2015). The promise and potential of e-assessment for learning. In P. Reimann, S. Bull, M. Kickmeier-Rust, R. Vatrapu, & B. Wasson (Eds.), *Measuring and Visualizing Learning in the Information-Rich Classroom* (pp. 21-40). New York: Routledge.

Richardson, J. T. E. (2009a). The academic attainment of students with disabilities in UK higher education. *Studies in Higher Education, 34*(2), 123-137. doi: 10.1080/03075070802596996

Richardson, J. T. E. (2009b). The attainment and experiences of disabled students in distance education. *Distance Education, 30*(1), 87-102. doi: 10.1080/01587910902845931

Richardson, J. T. E. (2012). The attainment of White and ethnic minority students in distance education. *Assessment & Evaluation in Higher Education, 37*(4), 393-408. doi: 10.1080/02602938.2010.534767

Richardson, J. T. E. (2013). The National Student Survey and its Impact on UK Higher Education. In M. Shah & C. S. Nair (Eds.), *Enhancing Student Feedback and Improvement Systems in Tertiary Education* (Vol. 5, pp. 76–84). Abu Dhabi, UAE: Commission for Academic Accreditation.

Richardson, J. T. E. (2014). Academic attainment of students with disabilities in distance education. *Journal of Postsecondary Education and Disability, 27*(3), 291-305. doi: 10.1080/0309877X.2013.858680

Richardson, J. T. E. (2015a). Coursework versus examinations in end-of-module assessment: a literature review. *Assessment & Evaluation in Higher Education, 40*(3), 439-455. doi: 10.1080/02602938.2014.919628

Richardson, J. T. E. (2015b). Quality Enhancement Report, Academic attainment in disabled students at The Open University. Milton Keynes: IET, Open University UK.

Richardson, J. T. E. (2015c). The under-attainment of ethnic minority students in UK higher education: what we know and what we don't know. *Journal of Further and Higher Education, 39*, 278-291. doi: 10.1080/0309877X.2013.858680

Rienties, B. (2014). Understanding academics' resistance towards (online) student evaluation. *Assessment & Evaluation in Higher Education, 39*(8), 987-1001. doi: 10.1080/02602938.2014.880777

Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action Evaluation Framework: a review of evidence-based learning analytics interventions at Open University UK. *Journal of Interactive Media in Education, 1*(2), 1-12. doi: 10.5334/jime.394

Rienties, B., Cross, S., & Zdrahal, Z. (2016). Implementing a Learning Analytics Intervention and Evaluation Framework: what works? In B. K. Daniel (Ed.), *Big Data and Learning Analytics in Higher Education: Current Theory and Practice* (pp. 147-166). Heidelberg: Springer.

Rienties, B., Li, N., & Marsh, V. (2015). Modeling and managing student satisfaction: use of student feedback to enhance learning experience *Subscriber Research Series 2015-16*. Gloucester: Quality Assurance Agency.

Rienties, B., & Toetenel, L. (2016). The impact of learning design on student behaviour, satisfaction and performance: a cross-institutional comparison across 151 modules. *Computers in Human Behavior, 60*, 333-341. doi: 10.1016/j.chb.2016.02.074

Rienties, B., Toetenel, L., & Bryan, A. (2015). "Scaling up" learning design: impact of learning design activities on LMS behavior and performance *5th Learning Analytics Knowledge conference* (pp. 315-319). New York: ACM.

Rogaten, J., Rienties, B., & Whitelock, D. (2016). *Assessing Learning Gains*. Paper presented at the TEA, Tallinn.

Rose-Adams, J., & Hewitt, L. (2012). 'What retention' means to me: the position of the adult learner in student retention. *Widening Participation and Lifelong Learning, 14*, 146-164.

Rowntree, D. (1987). *Assessing Students: How shall we know them?* London: Kogan Page.

Rust, C. (2011). The unscholarly use of numbers in our assessment practices: What will make us change? *International Journal for the Scholarship of Teaching and Learning, 5*(1), 4.

Rust, C. (2015). *The international state of research on assessment & examinations in Higher Education.* Paper presented at the Prüfungsforschung.

Sadler, D. R. (1989). Formative assessment and the design of instructional systems. *Instructional Science, 18*(2), 119-144. doi: 10.1007/bf00117714

Scanlon, E., McAndrew, P., & O'Shea, T. (2015). Designing for educational technology to enhance the experience of learners in distance education: How open educational resources, learning design and Moocs are influencing learning. *Journal of Interactive Media in Education, 2015*(1). doi: 10.5334/jime.al

Seale, J., Georgeson, J., Mamas, C., & Swain, J. (2015). Not the right kind of 'digital capital'? An examination of the complex relationship between disabled students, their

technologies and higher education institutions. *Computers & Education, 82*, 118-128. doi: 10.1016/j.compedu.2014.11.007
Segers, M., Dochy, F., & Cascallar, E. (2003). *Optimising new modes of assessment: in search of qualities and standards.* Dordrecht: Kluwer Academic Publishers.
Sharples, M., de Roock , R., Ferguson, R., Gaved, M., Herodotou, C., Koh, E., . . . Wong, L. H. (2016). Innovating Pedagogy 2016: Open University Innovation Report 5. Milton Keynes: The Open University.
Siemens, G., Dawson, S., & Lynch, G. (2013). *Improving the quality of productivity of the higher education sector: Policy and strategy for systems-level deployment of learning analytics*: Solarresearch.
Singh, M. (2015). *Global Perspectives on Recognising Non-Formal and Informal Learning: Why Recognition Matters*. New York: Springer Open.
Sloan, D., Heath, A., Hamilton, B., Kelly, B., Petrie, H., & Phipps, L. (2006). *Contextual web accessibility - maximizing the benefit of accessibility guidelines*. Paper presented at the Proceedings of the 2006 international cross-disciplinary workshop on Web accessibility (W4A): Building the mobile web: rediscovering accessibility?, Edinburgh, United Kingdom.
Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning Analytics in a data-rich context. *Computers in Human Behavior, 47*, 157-167. doi: 10.1016/j.chb.2014.05.038
Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2017). Adding dispositions to create pedagogy-based Learning Analytics. *Zeitschrift für Hochschulentwicklung*.
Toetenel, L., & Rienties, B. (2016a). Analysing 157 Learning Designs using Learning Analytic approaches as a means to evaluate the impact of pedagogical decision-making. *British Journal of Educational Technology, 47*(5), 981–992. doi: 10.1111/bjet.12423
Toetenel, L., & Rienties, B. (2016b). Learning Design – creative design to visualise learning activities. *Open Learning, 31*(3), 233-244. doi: 10.1080/02680513.2016.1213626
Universities UK. (2016). *Working in partnership: enabling social mobility in higher education*. London: Universities UK.
Van Zundert, M., Sluijsmans, D., & van Merriënboer, J. (2010). Effective peer assessment processes: Research findings and future directions. *Learning and Instruction, 20*(4), 270-279. doi: 10.1016/j.learninstruc.2009.08.004
Weller, M. (2014). *The Battle for Open: how openness won and why it doesn't feel like victory*. London: Ubiquity Press.
Werquin, P. (2007). Terms, Concepts And Models For Analysing The Value Of Recognition Programmes. Vienna, Austria: OECD.
Whitelock, D. (2007). Computer assisted formative assessment: supporting students to become more reflective learners. In C. P. Constantinou, Z. C. Zacharia, & M. Papaevripidou (Eds.), *Proceedings of the 8th International Conference on Computer Based Learning in Science (CBLIS '07)* (pp. 492-504). Crete, Greece: E-Media, University of Crete.
Whitelock, D. (2010). Activating Assessment for Learning: Are We on the Way with Web 2.0? *Web 2.0-Based E-Learning: Applying Social Informatics for Tertiary Teaching* (pp. 319-342): IGI Global.
Whitelock, D., & Cross, S. (2014). Assessment: Practice and Promise. Milton Keynes: Open University.
Whitelock, D., Richardson, J. T. E., Field, D., Van Labeke, N., & Pulman, S. (2014). *Designing and Testing Visual representations of Draft Essays for Higher Education Students*. Paper presented at the Learning Analytics Knowledge conference 2014, Indianapolis.
Whitelock, D., & Rienties, B. (2016). #Design4Learning: Designing for the Future of Higher Education. *Journal of Interactive Media in Education, 1*(1), 1-3. doi: 10.5334/jime.417

Whittaker, R. (2010). *Facilitating the Recognition of Prior Learning*. Glasgow: Toolkit.
Wiliam, D., & Black, P. (1996). Meanings and Consequences: a basis for distinguishing formative and summative functions of assessment? *British Educational Research Journal, 22*(5), 537-548. doi: 10.1080/0141192960220502
Wolff, A., Zdrahal, Z., Nikolov, A., & Pantucek, M. (2013). *Improving retention: predicting at-risk students by analysing clicking behaviour in a virtual learning environment.* Paper presented at the Proceedings of the Third International Conference on Learning Analytics and Knowledge, Indianapolis.
Yorke, M., Woolf, H., Stowell, M., Allen, R., Haines, C., Redding, M., . . . Walker, L. (2008). Enigmatic Variations: Honours Degree Assessment Regulations in the UK. *Higher Education Quarterly, 62*(3), 157-180. doi: 10.1111/j.1468-2273.2008.00389.x
Zerihun, Z., Beishuizen, J., & Os, W. (2012). Student learning experience as indicator of teaching quality. *Educational Assessment, Evaluation and Accountability, 24*(2), 99-111. doi: 10.1007/s11092-011-9140-4